APPENDIX

# Prospect Theory and the Brain

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OUTLINE



## INTRODUCTION TO PROSPECT THEORY

Whether we like it or not we face risk every day of our lives. From selecting a route home from work to selecting a mate, we rarely know in advance and with certainty what the outcome of our decisions will be. Thus, we are forced to make tradeoffs between the attractiveness (or unattractiveness) of potential outcomes and their likelihood of occurrence.

The lay conception of *risk* is associated with hazards that fill one with dread or are poorly understood (Slovic, 1987). Business managers, for example, tend to see risk not as a gamble but as a "challenge to be overcome" and see risk as increasing with the magnitude of potential losses (e.g., March and Shapira, 1987). Likewise, medical clinicians tend to see risk as exposure to loss or harm to oneself or others (Furby and Beyth-Marom, 1992). Decision theorists, in contrast, view risk as increasing with variance in the probability distribution of possible outcomes, regardless of whether a potential loss is involved. For example, a prospect that offers a 50–50 chance of paying $100 or nothing is more risky than a prospect that offers $50 for sure—even though the risky prospect entails no possibility of losing money. This core idea serves as the focus of discussion in Chapter 9, which discusses the many approaches to risk in the study of human and animal preferences.

Since the work of the American economist Frank Knight (1921), however, economists have distinguished *decisions under risk* from *decisions under uncertainty*. In decisions under risk, the decision maker knows with precision the probability distribution of possible outcomes, as when betting on the flip of a coin or entering a lottery with a known number of tickets. In decisions under uncertainty the decision maker is not provided such information but must assess the probabilities of potential outcomes with some degree of vagueness, as when betting on a victory by the home team or investing in the stock market. This distinction between risk and uncertainty is also developed at greater length in Chapter 9.

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In this chapter, we explore behavioral and neuroeconomic perspectives on decisions under risk in one specific intellectual tradition that has emerged over the last few decades at the border between economics and psychology. For simplicity, we will confine most of our attention to how people evaluate simple prospects with a single nonzero outcome that occurs with known probability (e.g., a 50−50 chance of winning $100 or nothing) though we will also mention extensions to multiple outcomes and to vague or unknown probabilities.

In the remainder of this section we provide a brief overview of economic models of decision making under risk (for a fuller treatment, see Chapters 1, 3, and 9), culminating in prospect theory (Kahneman and Tversky, 1979; Tversky and Kahneman, 1992), the most influential descriptive account that has emerged to date (see also Wakker, 2010). In subsequent sections, we provide an overview of various parameterizations of prospect theory's functions, and review methods for eliciting them. We next take stock of neuroeconomic studies of prospect theory, and then provide some suggested directions for future research.

## Historical Context

The origin of decision theory is traditionally traced to a correspondence between Pascal and Fermat in 1654 that laid the mathematical foundation of probability theory. Theorists asserted that decision makers ought to choose the option that offers the highest expected value (EV). Consider a prospect ($x$, $p$) that offers \$$x$ with probability $p$ (and nothing otherwise):

$$EV = px. \tag{A.1}$$

A decision maker is said to be *risk neutral* if he is indifferent between a gamble and its expected value; he is said to be *risk averse* if he prefers a sure payment to a risky prospect of equal or higher expected value; he is said to be *risk seeking* if he prefers a risky prospect to a sure payment of equal or higher expected value. Thus, expected value maximization assumes a neutral attitude toward risk. For instance, a decision maker who employs this rule will prefer receiving $100 if a fair coin lands heads (and nothing otherwise) to a sure payment of $49, because the expected value of the gamble ($50 = .5 × $100) is higher than the value of the sure thing ($49).

Expected value maximization is problematic because it does not allow decision makers to exhibit risk aversion — it cannot explain, for example, why a person would prefer a sure $49 over a 50−50 chance of receiving $100 or nothing, or why anyone would purchase insurance. Swiss mathematician Daniel Bernoulli (1738) advanced a solution to this problem when he asserted that people do not evaluate options by their objective value but rather by their *utility* or "moral value." Bernoulli observed that a particular amount of money (say, $1000) is valued more when a person is poor (wealth level $W_1$) than when he is wealthy ($W_2$), and therefore marginal utility of gaining $1000 decreases (from $U_1$ to $U_2$) as wealth increases (see Figure A.1A). This gives rise to a utility function that is concave over states of wealth. In Bernoulli's model, decision makers choose the option with highest expected utility (EU):

$$EU = pu(x) \tag{A.2}$$

where $u(x)$ represents the utility of obtaining outcome $x$. For example, a concave utility function ($u''(x) < 0$) implies that the utility gained by receiving $50 is more than half the utility gained by receiving $100, and therefore a decision maker with such a utility function

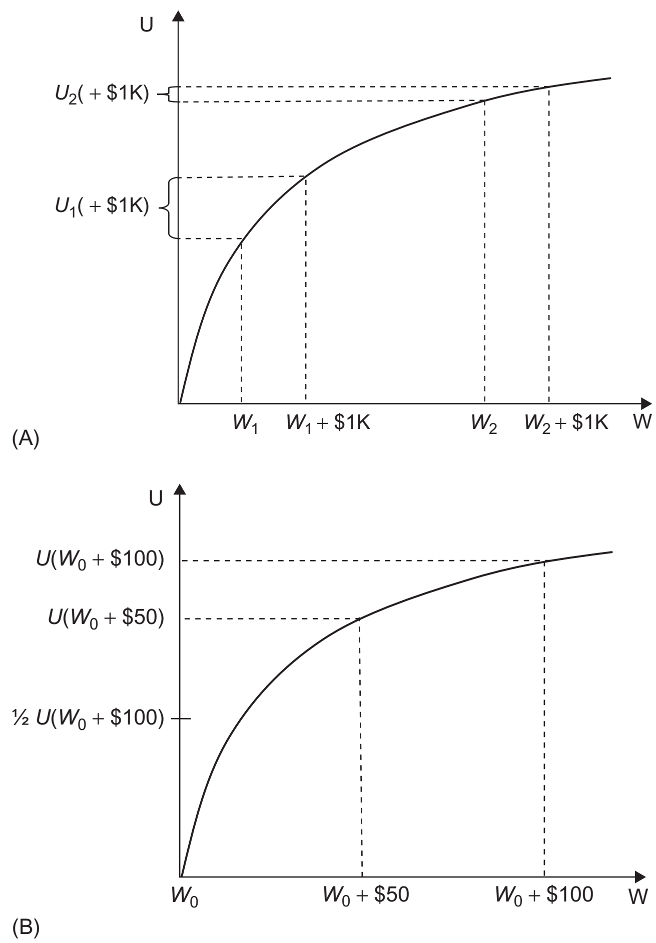


FIGURE A.1 (A) A representative utility function over states of wealth illustrating the notion of diminishing marginal utility. (B) A representative utility function over states of wealth illustrating risk aversion for gains at an initial state of wealth $W_0$.

should prefer \$50 for sure to a .5 probability of receiving \$100 (see Figure A.1B).

### *Axiomatization of Expected Utility*

Expected utility became a central component of economic theory when von Neumann and Morgenstern (1947) articulated a set of axioms that are both necessary and sufficient for representing a decision maker's choices by the maximization of expected utility (see also Jensen, 1967).

One of the central axioms of expected utility theory is the *substitution axiom* (a.k.a. "independence"): if a person prefers lottery $L_1$ to lottery $L_2$, then this preference should be not affected by a mixture of both lotteries with a common third lottery $L_3$. Formally, if $\succcurlyeq$ is a binary preference relation over lotteries, for any $\alpha \in (0, 1)$, $L_1 \succcurlyeq L_2$ if and only if $\alpha L_1 + (1-\alpha)L_3 \succcurlyeq \alpha L_2 + (1-\alpha)L_3$.

A more general formulation of expected utility theory that extended the model from risk to uncertainty (Savage, 1954) relies on a related axiom known as the *sure-thing principle*: if two options yield the same consequence when a particular event occurs, then a person's preferences among those options should not depend on the particular consequence (i.e., the "sure thing") or the particular event that they have in common. To illustrate, consider a game show in which a coin is flipped to determine where a person will be sent on vacation. Suppose the contestant would rather go to Atlanta if the coin lands heads and Chicago if it lands tails ($a$, $H$; $c$, $T$) than go to Boston if the coin lands heads and Chicago if it lands tails ($b$, $H$; $c$, $T$). If this is the case, he should also prefer to go to Atlanta if the coin lands heads and Detroit (or any other city for that matter) if the coin lands tails ($a$, $H$; $d$, $T$) to Boston if it lands heads and Detroit if it lands tails ($b$, $H$; $d$, $T$).

### *Violations of Substitution and the Sure Thing Principle*

It was not long before the descriptive validity of expected utility theory and its axioms were called into question. One of the most powerful challenges has come to be known as the *Allais paradox* (Allais, 1953; Allais and Hagen, 1979). The following version was presented by Kahneman and Tversky (1979).[1]

> **Decision 1:** Choose between (A) an 80% chance of \$4000; (B) \$3000 for sure.
> **Decision 2:** Choose between (C) a 20% chance of \$4000; (D) a 25% chance of \$3000.

Most respondents chose (B) over (A) in the first decision and (C) over (D) in the second decision, which violates the substitution axiom. To see why, note that $C = \frac{1}{4}A$ and $D = \frac{1}{4}B$ so that according to the substitution axiom a decision maker should prefer $C$ to $D$ if and only if he prefers $A$ to $B$. This systematic violation of substitution is known as the *common ratio effect*.

**TABLE A.1** The Allais Common Consequence Effect Represented Using a Lottery with Numbered Tickets.

| | Ticket numbers | | |
|---|---|---|---|
| **Option** | **1–33** | **34** | **35–100** |
| E | 2500 | 0 | 2400 |
| F | 2400 | 2400 | 2400 |
| G | 2500 | 0 | 0 |
| H | 2400 | 2400 | 0 |

A related demonstration from Allais was adapted by Kahneman and Tversky (1979) as follows:

> **Decision 3:** Choose between (E) a 33% chance of \$2500; a 66% chance of \$2400 and a 1% chance of nothing; (F) \$2400 for sure.
> **Decision 4:** Choose between (G) a 33% chance of \$2500; (H) a 34% chance of \$2400.

In this case most people prefer option (F) to option (E) in Decision 3, but they prefer option (G) to option (H) in Decision 4, which violates the sure-thing principle. To see why, consider options (E) through (H) as being payment schemes attached to different lottery tickets that are numbered consecutively from 1 to 100 (see Table A.1). Note that one can transform options (E) and (F) into options (G) and (H), respectively, merely by replacing the common consequence (receive \$2400 if the ticket drawn is 35–100) with a new common consequence (receive \$0 if the ticket drawn is 35–100). Thus, according to the sure-thing principle, a person should favor option (G) over option (H) if and only if he prefers option (E) to option (F), and the dominant pattern of preferences violates this axiom. This violation of the sure-thing principle is known as the *common consequence effect*.

Both the common ratio effect and common consequence effect resonate with the notion that people are more sensitive to differences in probability near impossibility and certainty than in the intermediate range of the probability scale. Thus, people typically explain their choice in Decision (1) as a preference for certainty over a slightly smaller prize that entails a possibility of receiving nothing; meanwhile, they explain their choice in Decision (2) as a preference for a higher possible prize given that the difference between a probability of .20 and .25 is not very large.

[1]Kahneman and Tversky's version was originally denominated in Israeli Pounds.

Likewise, people explain their choice in Decision (3) as a preference for certainty over a possibility of receiving nothing; meanwhile, they explain their choice in Decision (2) as a preference for a higher possible prize given that the difference between a probability of .33 and .34 seems trivial.

### *The Fourfold Pattern of Risk Attitudes*

The Allais paradox is arguably the starkest and most celebrated violation of expected utility theory to date. In the years since it was articulated, numerous studies of decision under risk have shown that people often violate the principle of risk aversion that underlies much economic analysis. Table A.2A illustrates a common pattern of risk aversion and risk seeking exhibited by participants in studies of Tversky and Kahneman (1992). Let $c(x, p)$ be the *certainty equivalent* of the prospect $(x, p)$ that offers to pay \$$x$ with probability $p$ (i.e., the sure payment that is deemed equally attractive to the risky prospect). The upper left-hand entry in Table A.2A shows that the median participant was indifferent between receiving \$14 for sure and a 5% chance of gaining \$100. Because the expected value of the prospect is only \$5, this observation reflects risk seeking behavior.

Table A.2A reveals a four-fold pattern of risk attitudes: risk seeking for low-probability gains and high-probability losses, coupled with risk aversion for high-probability gains and low-probability losses. Choices consistent with this fourfold pattern have been observed in several studies (Fishburn and Kochenberger, 1979; Kahneman and Tversky, 1979; Hershey and Schoemaker, 1980; Payne *et al*., 1981). Risk seeking for low-probability gains may contribute to the attraction of gambling, whereas risk aversion for low-probability losses may contribute to the attraction of insurance. Risk aversion for high-probability gains may contribute to the preference for certainty, as in the Allais (1953) paradox, whereas risk seeking for high-probability losses is consistent with the common tendency to undertake risk to avoid facing a sure loss.

**TABLE A.2A** The Fourfold Pattern of Risk Attitudes

| | Gains | Losses |
|---|---|---|
| Low probability | $c(\$100, .05) = \$14$ | $c(-\$100, .05) = -\$8$ |
| | *Risk seeking* | *Risk aversion* |
| High probability | $c(\$100, .95) = \$78$ | $c(-\$100, .95) = -\$84$ |
| | *Risk aversion* | *Risk seeking* |

$c(x, p)$ is the median certainty equivalent of the prospect that pays \$$x$ with probability $p$.
*Table A.2A adapted from Tversky and Kahneman (1992).*

## Prospect Theory

The Allais paradox and the four-fold pattern of risk attitudes are accommodated neatly by prospect theory (Kahneman and Tversky, 1979; Tversky and Kahneman, 1992), the leading behavioral model of decision making under risk, and the major work for which Daniel Kahneman was awarded the 2002 Nobel Prize in economics (his colleague Amos Tversky passed away in 1996 and was therefore not eligible but was featured prominently in the citation).

According to prospect theory, the value $V$ of a simple prospect that pays \$$x$ with probability $p$ (and nothing otherwise) is given by:

$$V(x, p) = w(p)v(x), \tag{A.3}$$

where $v$ measures the subjective value of the consequence $x$, and $w$ measures the impact of probability $p$ on the attractiveness of the prospect (see Figure A.2).

### *Value Function*

Prospect theory replaces the utility function $u(\cdot)$ over states of wealth described in Chapters 1, 3, and 9 with a value function $v(\cdot)$ over gains and losses relative to a reference point, with $v(0) = 0$. According to prospect theory, the value function $v(\cdot)$ exhibits the psychophysics of diminishing sensitivity. That is, the marginal impact of a change in value diminishes with the distance from a relevant reference point, so that the function is concave for gains and convex for losses (see Figure A.2A). For monetary outcomes, the *status quo* generally serves as the reference point distinguishing losses from gains, though a decision-maker's goals (Heath *et al*., 1999) or expectations (Kőszegi and Rabin, 2006) may also provide reference points. (Note that

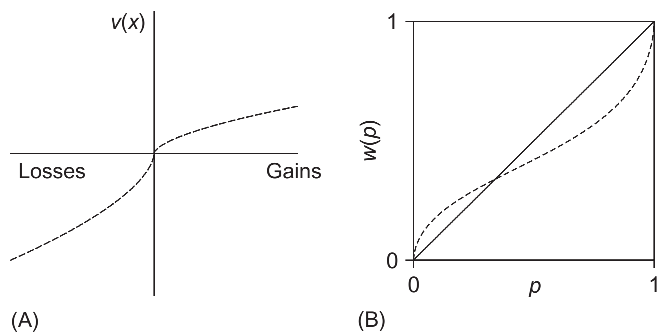


**FIGURE A.2** Representative value function (A) and weighting function (B) from prospect theory. (A) A prospect theory value function illustrating concavity for gains, convexity for losses, and a steeper loss than gain limb. (B) A prospect theory weighting function illustrating its characteristic inverse-S shape, the tendency to overweight low probabilities and underweight moderate to large probabilities, and the tendency for weights of complementary probabilities to sum to less than one.

Chapter 24 provides a more detailed discussion of reference dependency.) Concavity for gains contributes to risk aversion for gains, as with the standard utility function (Figure A.1). Convexity for losses, on the other hand, contributes to risk seeking for losses. For instance, the disvalue of losing $50 is more than half the disvalue of losing $100, which will contribute to a preference for the gamble over the sure loss. This tendency to be risk averse for moderate-probability gains and risk seeking for moderate-probability losses may contribute to the *disposition effect* in which investors have a greater tendency to sell stocks in their portfolios that have risen rather than fallen since purchase (Odean, 1998; but see also Barberis and Xiong, 2009).

The prospect theory value function is steeper for losses than gains, a property known as *loss aversion*. People typically require more compensation to give up a possession than they would have been willing to pay to obtain it in the first place (see, for example, Kahneman *et al*., 1990 and Chapter 3). In the context of decision under risk, loss aversion gives rise to risk aversion for mixed (gain−loss) gambles so that, for example, people typically reject a gamble that offers a .5 chance of gaining $100 and a .5 chance of losing $100, and require at least twice as much "upside" as "downside" to accept such gambles (see Table A.2B). In fact, Rabin (2000) showed that a concave utility function over states of wealth cannot explain the normal range of risk aversion for mixed gambles, because this implies that a decision maker who is mildly risk averse for small-stakes gambles over a range of states of wealth must be unreasonably risk averse for large-stakes gambles — a phenomenon sometimes called the *Rabin paradox*. This tendency to be risk-averse for mixed prospects has been used by Benartzi and Thaler (1995) to explain why investors require a large premium to invest in stocks rather than bonds (an important phenomenon in economics known as the *equity premium puzzle*): because of the higher volatility of stocks, investors who frequently check their returns are more likely to experience a decrease in nominal value of their portfolios the more they invest in stocks (see also Barberis *et al*., 2001).

**TABLE A.2B** Risk Aversion for Mixed (Gain−Loss) Gambles

| Gain | Loss | Ratio |
|---|---|---|
| 61 | 25 | 2.44 |
| 101 | 50 | 2.02 |
| 202 | 100 | 2.02 |
| 280 | 150 | 1.87 |

Gain amounts for which the median participant found 50−50 mixed gambles equally attractive to receiving nothing, listed by loss amount.
*Table A.2B adapted from Tversky and Kahneman (1992).*

It is important to note that loss aversion, which gives rise to risk aversion for mixed, or gain−loss, prospects (most people reject a 50−50 chance to gain $100 or lose $100) should be distinguished from convexity of the value function for losses, which gives rise to risk-seeking for pure loss prospects (most people would rather face a 50−50 chance of losing $100 or nothing, than losing $50 for sure).

### *Weighting Function*

In prospect theory, the value of an outcome is weighted not by its probability but instead by a decision weight, $w(\cdot)$, that represents the impact of the relevant probability on the valuation of the prospect. Decision weights are normalized so that $w(0) = 0$ and $w(1) = 1$. Note that $w$ need not be interpreted as a measure of subjective belief — a person may report that they believe that the probability of a fair coin landing heads is one-half, but afford this event a weight of less than one-half in the evaluation of a prospect.

Just as the value function captures diminishing sensitivity to changes in the number of dollars gained or lost, the weighting function captures diminishing sensitivity to changes in probability. For probability, there are two natural reference points: impossibility and certainty. Hence, diminishing sensitivity implies an inverse-*S*-shaped weighting function that is concave near zero and convex near one, as depicted in Figure A.2B. It can help explain the fourfold pattern of risk attitudes (Table A.2A), because moderate to high probabilities are underweighted (which reinforces the pattern of risk aversion for gains and risk seeking for losses implied by the shape of the value function) and low probabilities are overweighted (which reverses the pattern implied by the value function and leads to risk seeking for gains and risk aversion for losses).

To appreciate the intuition underlying how the value and weighting functions contribute to the fourfold pattern, refer to Figure A.2B. Informally, the reason that most participants in Tversky and Kahneman's (1992) sample would rather have a .95 chance of $100 than $77 for sure is partly because they find receiving $77 nearly as appealing as receiving $100 (i.e., the slope of the value function decreases with dollars gained), and partly because a .95 chance "feels" like a lot less than a certainty (i.e., the slope of the weighting function is high near one). Likewise, most participants would rather face a .95 chance of losing $100 than pay $85 for sure, partly because paying $85 is almost as painful as paying $100 and partly because a .95 chance "feels" like it is much less than certain. On the other hand, the reason that most participants would rather have a .05 chance of $100 than $13 for sure is that a .05 chance "feels" like more than no chance at all (i.e., the slope of the weighting function is steep near zero) – in fact it "feels" like more than its objective probability, and this distortion is more pronounced than the feeling that receiving $13 is more than 13% as attractive as receiving $100. Likewise, the reason most participants would rather lose $7 for sure than face a .05 chance of losing $100 is that the .05 chance of losing money looms larger than its respective probability, and this effect is more pronounced than the feeling that receiving $7 is more than 7% as attractive as receiving $100.

The inverse-S-shaped weighting function also explains the Allais paradox because the ratio of weights of probabilities .8 and 1 is smaller than the ratio of weights of probabilities .20 and .25 (so that the difference between a .80 chance of a prize and a certainty of a prize in Decision 1 looms larger than the difference between a .20 and .25 chance of a prize in Decision 2); similarly, the difference in the weights of probabilities .99 and 1 is larger than the difference in the weights of probabilities .33 and .34 (so that the difference between a .99 chance and a certainty of receiving a large prize in Decision 3 looms larger than the difference between a .33 chance and a .34 chance in Decision 4). This inverse-S-shaped weighting function seems to be consistent with a range of empirical findings in laboratory studies (Camerer and Ho, 1994; Tversky and Fox, 1995; Wu and Gonzalez, 1996, 1998; Gonzalez and Wu, 1999; Wakker, 2001). Overweighting of low-probability gains can help explain why the attraction of lotteries tends to increase as the top prize increases even as the chances of winning decreases correspondingly (Cook and Clotfelter, 1993), the attraction to longshot bets over favorites in horse races, and the overpricing of securities with positively skewed returns (Barberis and Huang, 2008). Overweighting of low-probability losses can explain the attractiveness of insurance (Wakker *et al*., 1997).

In sum, prospect theory explains attitudes toward risk via distortions in shape of the value and weighting functions. The data of Tversky and Kahneman (1992) suggest that the four-fold pattern of risk attitudes for simple prospects that offer a gain or a loss with low or high probability (Table A.2A) is driven primarily by curvature of the weighting function, because the value function is not especially curved for the typical participant in those studies. Pronounced risk aversion for mixed prospects that offer an equal probability of a gain or loss (Table A.2B) is driven almost entirely by loss aversion because the curvature of the value function is typically similar for losses versus gains and decision weights are similar for gain versus loss components (see also Novemsky and Kahneman, 2005).

### *Framing, Editing, and Bracketing*

Expected utility theory and most normative models of decision making under risk assume *description invariance*: preferences among prospects should not be affected by how they are described. Decision makers act as if they are assessing the impact of options on final states of wealth. Prospect theory, in contrast, explicitly acknowledges that choices are influenced by how prospects are cognitively represented in terms of losses and gains and their associated probabilities. There are three important manifestations of this principle.

First, this representation can be systematically influenced by the way in which options are described or *framed*, a point also developed in Chapters 3 and 24. Recall that the value function is applied to a reference point that distinguishes between losses and gains. A common default reference point is the *status quo*. However, by varying the description of options one can influence how they are perceived. For instance, decisions concerning medical treatments can differ depending on whether possible outcomes are described in terms of survival versus mortality rates (McNeil *et al*., 1982); recall that people tend to be risk averse for moderate probability gains and risk seeking for moderate probability losses. Likewise, the weighting function is applied to probabilities of risky outcomes that a decision maker happens to identify. The description of gambles can influence whether probabilities are integrated or segregated and therefore affect the decisions that people make (Tversky and Kahneman, 1986). For instance, people have been shown to be more likely to favor a .25 chance of $32 over a .20 chance of $40 when this choice was described as a two-stage game in which there was a .25 chance of obtaining a choice between $32 for sure or an .80 chance of $40 (i.e., the $32 outcome was more attractive when it was framed as a certainty). People may endogenously frame prospects in ways that are not apparent to observers, adopting aspirations as reference points (Heath *et al*., 1999), incorporating expectations into reference point setting (Kőszegi and Rabin, 2006; Post *et al*., 2008), or persisting in the adoption of prior reference points, viewing recent winnings as house money (Thaler and Johnson, 1990).

Second, people may mentally transform or 'edit' the description of prospects they have been presented. The original formulation of prospect theory (Kahneman and Tversky, 1979) suggested that decision makers edit prospects in forming their subjective representation. Consider prospects of the form ($\$x_1$, $p_1$; $\$x_2$, $p_2$; $\$x_3$, $p_3$) that offer $\$x_i$ with (disjoint) probability $p_i$ (and nothing otherwise). In particular, decision makers are assumed to engage in the following mental transformations:

1. *Combination*. Decision makers tend to simplify prospects by combining common outcomes – for example, a prospect that offers ($10, .1; $10, .1) would be naturally represented as ($10, .2);

2. *Segregation.* Decision makers tend to segregate sure outcomes from the representation of a prospect – for instance, a prospect that offers ($20, .5; $30, .5) would be naturally represented as $20 for sure plus a ($10, .5);
3. *Cancellation.* Decision makers tend to cancel shared components of options that are offered together – for example, a choice between ($10, .1; $50, .1) or ($10, .1; $20, .2) would be naturally represented as a choice between a ($50, .1) or ($20, .2);
4. *Rounding.* Decision makers tend to simplify prospects by rounding uneven numbers or discarding extremely unlikely outcomes – for example, ($99, .51; $5, .0001) might be naturally represented as ($100, .5);
5. *Transparent dominance.* Decision makers tend to reject options without further evaluation if they are obviously dominated by other options – for instance, given a choice between ($18, .1; $19, .1; $20, .1) or ($20, .3), most people would naturally reject the first option because it is stochastically dominated by the second.

In addition to the effects of framing and editing, the evaluation period over which choices are "bracketed" may influence risk preferences (Read *et al*., 1999). For instance, participants receiving feedback on the outcome of multiple decisions over longer evaluation windows may be more risk-neutral than participants receiving feedback on the outcome of each decision immediately after it is made (Benartzi and Thaler, 1995; Gneezy and Potters, 1997).

## Applications to Riskless Choice

Although prospect theory was originally developed as an account of decision making under risk, many manifestations of this model in riskless choice have been identified in the literature.

### *Loss Aversion*

Loss aversion implies that preferences among consumption goods will systematically vary with one's reference point (Kahneman and Tversky, 1991; see also Bateman *et al*., 1997), which has several manifestations. First, the minimum amount of money a person is *willing to accept* (WTA) to part with an object generally exceeds the minimum amount of money that he is *willing to pay* (WTP) to obtain the same object. This pattern, robust in laboratory studies using student populations and ordinary consumer goods, is even more pronounced for non-market goods, non-student populations, and when incentives are included to encourage non-strategic responses (Horowitz and McConnell, 2002).

Likewise, people tend to value objects more highly after they come to feel that they own them, a phenomenon known as the *endowment effect* (Thaler, 1980). For instance, in one well-known study Kahneman and colleagues (1990) presented a coffee mug with a university logo to one group of participants ("sellers") and told them the mug was theirs to keep, then asked these participants whether they would sell the mug back to them at various prices. A second group of participants ("choosers") were told that they could have the option of receiving an identical mug or an amount of money and asked which they preferred at various prices. Although both groups were placed in strategically identical situations (walk away with a mug or money), the sellers, who presumably framed the choice as a loss of a mug against a compensating gain of money, quoted a median price of $7.12, whereas the choosers, who presumably framed the choice as a gain of a mug against a gain of money, quoted a median price of $3.12.[2]

Loss aversion is thought to contribute to the inertial tendency to stick with status quo options (Samuelson and Zeckhauser, 1988) and the reluctance to trade. For instance, in one study Knetsch (1989) provided students a choice between a university mug and a bar of Swiss chocolate and found that they had no significant preference for one over the other. However, when some students were assigned at random to receive the mug and given an opportunity to trade for the chocolate, 89% retained the mug; when other students were assigned at random to receive the chocolate and given an opportunity to trade for the mug, only 10% opted for the mug.

Loss aversion has been invoked to help explain a number of anomalous patterns in field data. Notably, loss aversion can partly account for the powerful attraction of defaults on behavior – for instance, why organ donation rates are much higher for European countries with an *opt-out policy* than those with an

[2]Plott and Zeiler (2005) claimed that the endowment effect is an experimental artifact of the particular instructions to participants who have "misconceptions about the nature of the experimental task" (p. 542). They found that in a variation in which participants are provided with anonymity and a detailed explanation of and practice with the Becker–DeGroot–Marschak incentive-compatible mechanism used to derive valuations, the gap between selling and buying prices disappears in a similar "mugs" experiment. However, Isoni and colleagues (2011) observed that the gap between buyers and sellers persists for lotteries using this modified procedure, and they speculate that Plott and Zeiler's experimental design may introduce new artifacts that "dampen . . . disparities by reducing the salience of the distinction between buying and selling tasks."

*opt-in policy* (Johnson and Goldstein, 2003), the tendency of consumer demand to be more sensitive to price increases than decreases (Hardie *et al*., 1993), and the tendency for taxi drivers to quit after they have met their daily income targets, even on busy days during which their hourly wages are higher (Camerer *et al*., 1997). In fact, Fehr and Goette (2007) found a similar pattern among bicycle messengers in which only those who exhibited loss-averse preferences for mixed gambles tended to exert more effort per hour when their wage per completed job decreased. Interestingly, professional golfers appear to be more accurate when attempting putts that would earn them a score at or over par than when attempting similar putts that would earn them a score below par, suggesting that loss aversion for hole-by-hole scores influences focus and effort (Pope and Schweitzer, 2011).

The stronger response to losses than foregone gains also manifests itself in evaluations of fairness. In particular, most people find it unfair for an employer or merchant to raise prices on consumers or to lower wages for workers unless the employer or merchant is defending against losses of their own, and this places a constraint on profit seeking even when the market clearing price (wage) goes up (down; Kahneman *et al*., 1986). For instance, people find it more fair to take away a rebate than to impose a price increase on customers; most people think it is unfair for a hardware store to exercise their economic power by raising the price of snow shovels after a snowstorm.

Loss aversion is also evident in riskless choice when consumers face tradeoffs of one product attribute against one another. For instance, Kahneman and Tversky (1991) asked participants to choose between two hypothetical jobs: Job $x$ was characterized as "limited contact with others" and a 20-minute daily commute; Job $y$ was characterized as "moderately sociable" with a 60-minute daily commute. Participants were much more likely to choose Job $x$ if they had been told that their present job was socially isolated with a 10-minute commute than if they had been told it was very social but had an 80-minute commute, consistent with the notion that they are loss averse for attributes that present relative advantages and disadvantages. Loss aversion when making tradeoffs may partially explain the ubiquity of brand loyalty in the marketplace.

Given the disparate manifestations of loss aversion, it is natural to ask to what extent there is any consistency in a person's degree of loss aversion across these different settings. Gächter *et al.* (2010) approached customers of a car manufacturer and, through a series of simple tasks, determined each customer's coefficient of loss aversion in a risky context, as well as a measure of the endowment effect that compares the minimum amount of money each participant was willing to accept to give up a model car and their maximum willingness to pay to acquire the model car. Remarkably, the Spearman correlation between the risky and riskless measures was .64, suggesting some consistency in the underlying trait of loss aversion.[3]

### *Curvature of the Value Function*

Not only does the difference in steepness of the value function for losses versus gains affect riskless choice, but so does the difference in curvature. Notably, Heath *et al*. (1999) asserted that goals can serve as reference points that inherit properties of the prospect theory value function. For instance, most people believe that a person who has completed 42 sit-ups would be willing to exert more effort to complete one last sit-up if he had set a goal of 40 than if he had set a goal of 30, because the value function is steeper (above the reference point) in the former than in the latter case. Conversely, most people believe that a person who has completed 28 sit-ups would be willing to exert more effort to complete one last sit-up if he had set a goal of 30 than if he had set a goal of 40, because value function is steeper (below the reference point) in the former case than the latter case.

The cognitive activities that people use to frame and package gains and losses, known as *mental accounting* (Thaler, 1980, 1985, 1999), can influence the way in which riskless outcomes are experienced. In particular, due to the concavity of the value function for gains, people derive more enjoyment when gains are segregated (e.g., it feels better to win two lotteries on two separate days); due to the convexity of the value function for losses, people find it less painful when losses are integrated (e.g., it feels better to pay a parking ticket the same day I pay my taxes) — but see Linville and Fischer (1991).

## Extensions to Uncertainty

As mentioned earlier, decision theorists distinguish between decisions under risk, in which probabilities are known to the decision maker, and decisions under uncertainty, in which they are not. This distinction is of critical importance because many investigations of decision-making in naturalistic contexts (such as financial, legal, and medical decisions) and many empirical paradigms (including many brain imaging studies)

[3]We note, however, that Abdellaoui *et al*. (2013b) did not find a strong relationship between loss aversion measured in a risky choice versus inter-temporal choice context.

entail decisions in which participants are not presented simple and clearly defined chance gambles. Thus, researchers wishing to understand behavior in these contexts must understand complications that arise under uncertainty.

The original formulation of prospect theory (henceforth known as OPT; Kahneman and Tversky, 1979) applies to decisions under risk and involving at most two nonzero outcomes. *Cumulative prospect theory* (henceforth CPT; Tversky and Kahneman, 1992; see also Luce and Fishburn, 1991; Wakker and Tversky, 1993) accommodates decisions under uncertainty and any finite number of possible outcomes.[4] A thorough account of CPT is beyond the scope of this chapter, we will only sketch out its distinctive features. Interested readers should refer to the original paper (Tversky and Kahneman, 1992) for further details.

### *Cumulative Prospect Theory*

When considering simple chance prospects with at most two nonzero outcomes, two distinctive features of CPT are important.

First, cumulative prospect theory segregates value into gain portions and loss portions, with separate weighting functions for losses and gains (i.e., CPT decision weights are *sign-dependent*).[5]

Second, CPT applies decision weights to cumulative distribution functions rather than single events (i.e., CPT decision weights are *rank-dependent*, as in a *rank-dependent utility theory* as discussed in Chapter 9).[6] That is, each outcome $x$ is weighted not by its probability but by the cumulated probabilities of obtaining an outcome at least as good as $x$ if the outcome is positive, and at least as bad as $x$ if it the outcome is negative.

More formally, consider a chance prospect with two nonzero outcomes $(x, p; y, q)$ that offers \$$x$ with probability $p$ and \$$y$ with probability $q$ (otherwise nothing). Let $w^+(\cdot)$ and $w^-(\cdot)$ be the weighting function for gains and losses, respectively. The CPT valuation of the prospect is given by:

$$w^-(p)v(x) + w^+(q)v(y), \quad \text{for mixed prospects, } x < 0 < y \tag{A.4}$$

$$[w^+(p+q) - w^+(q)]v(x) + w^+(q)v(y) \quad \text{for pure gain prospects, } 0 \leq x < y \tag{A.5}$$

$$[w^-(p+q) - w^-(q)]v(x) + w^-(q)v(y) \quad \text{for pure loss prospects, } y < x \leq 0. \tag{A.6}$$

The first equation illustrates sign dependence: a different weighting function is applied separately to the loss and gain portions of mixed prospects. The second and third equations illustrate rank dependence for gains and losses, respectively: extreme ($y$) outcomes are weighted by the impact of their respective probabilities, whereas intermediate outcomes ($x$) are weighted by the difference in impact of the probability of receiving an outcome at least as good as $x$ and the impact of the probability of receiving an outcome that is strictly better than $x$. A more general characterization of CPT that applies to any finite number of outcomes and decisions under uncertainty is included in Box 1 at end of this chapter.

For decision under risk, the predictions of CPT coincide with OPT for all two-outcome risky prospects and all mixed (gain−loss) three-outcome prospects[7] when one outcome is zero, assuming $w^+ = w^-$. Because elicitation of prospect theory parameters (reviewed in the following section) usually requires the use of two-outcome prospects, we illustrate how they coincide for a two-outcome (pure gain) prospect below. Consider a prospect $(x, p; y)$ that offers \$$x$ with probability $p$ and otherwise \$$y$, where $x > y$. According to CPT:

$$V(x, p; y) = [1 - w(p)]\, v(y) + w(p)\, v(x). \tag{A.7}$$

[4]The distinction between OPT and CPT is an important one that is often under-appreciated by those outside decision theory. For a discussion of the limitations of CPT to finite discrete distributions and an extension to continuous distributions see Rieger and Wang (2008).

[5]Wu and Markle (2008) document systematic violations of gain-loss separability. Their results suggest slightly different weighting function parameter values for mixed (gain−loss) prospects than for single domain (pure gain or pure loss) prospects. See also Birnbaum and Bahra (2007).

[6]Rank-dependence is motivated in part by the concern that nonlinear decision weights applied directly to multiple simple outcomes can give rise to violations of stochastic dominance. For instance, a prospect that offers a .01 chance of \$99 and a .01 chance of \$100 might be preferred to a prospect that offers a .02 chance of \$100 due to the overweighting of low probabilities, even though the latter prospect dominates the former prospect. OPT circumvents this problem for simple prospects by assuming that transparent violations of dominance are eliminated in the editing phase; CPT handles this problem through rank-dependent decision weights that sum to one for pure gain or loss prospects. For further discussion of advantages of CPT over OPT when modeling preferences involving complex prospects, see Fennema and Wakker (1997).

[7]Gonzalez and Wu (2003) estimated prospect theory weighting functions and value functions obtained from certainty equivalents for two-outcome gambles, in which OPT and CPT coincide, and applied these estimates to predict certainty equivalents for three-outcome gambles, in which they do not. Interestingly, they found systematic over-prediction for OPT and systematic under-prediction for CPT.

According to OPT, decision makers tend to invoke the editing operation of *segregation*, treating the smaller outcome $y$ as a certainty, and reframing the prospect as a $p$ chance of getting an additional $x-y$. Thus, we get:

$$V(x, p; y) = v(y) + w(p)[v(x) - v(y)], \tag{A.8}$$

which can be rearranged into the same expression as above. It is also easy to see that when $y = 0$, $V(x,p) = w(p)\, v(x)$ under both CPT and OPT.

### Weighting Probabilities: The Two-Stage Model

As we have seen, the risky weighting function is assumed to exhibit greater sensitivity to changes in probability (i.e., higher slope) near the natural boundaries of 0 and 1 than in the midpoint of the scale. A characterization of the weighting function that generalizes this observation from risk to uncertainty through the measure of *bounded subadditivity* is presented in Tversky and Fox (1995); see also Tversky and Wakker (1995), Wu and Gonzalez (1999). Informally, bounded subadditivity quantifies a decision maker's diminished sensitivity to events when they are added or subtracted from intermediate events compared to when they are added to impossibility or subtracted from certainty.

Several studies suggest that decisions under uncertainty accord well with a two-stage model in which participants first judge the likelihood of events on which outcomes depend, then apply the inverse-S shaped weighting function to these probabilities, consistent with prospect theory (Tversky and Fox, 1995; Fox and Tversky, 1998; for a theoretical treatment see Wakker, 2004). That is, the uncertain decision weight $W$ of event $E$ is given by

$$W(E) = w(P(E)), \tag{A.9}$$

where $P(E)$ is the (nonadditive) judged probability of event $E$ and $w(\cdot)$ is the risky weighting function. For instance, consider the prospect "win \$100 if the Los Angeles Lakers beat the Boston Celtics." A person's decision weight of "Lakers beat the Celtics" can be predicted well from his risky weighting function applied to his judged probability of the event "Lakers beat the Celtics." Judged probabilities are assumed to accord with support theory (Tversky and Koehler, 1994; Rottenstreich and Tversky, 1997), a behavioral model that conceives of judged probability as the proportion of support that a person associates with a focal hypothesis (for example, the Lakers will win) against its complement (the Celtics will win). Fox and Tversky (1998) review several studies that demonstrate the predictive validity of the two-stage model (see also Wu and Gonzalez, 1999; Fox and See, 2003; but see also Kilka and Weber, 2001).

### Ambiguity Aversion and Source Preferences

Decisions under uncertainty can be further complicated by a decision-maker's preference to bet on a particular source of uncertainty. Ellsberg (1961) observed that people prefer to bet on events with known rather than unknown probabilities, a phenomenon known as *ambiguity aversion* (for a review, see Chapter 3 and Camerer and Weber, 1992; see also Fox and See, 2003). This phenomenon may partially explain, for example, the common preference to invest in the domestic stock market and under-diversify into foreign markets (French and Poterba, 1991). Ambiguity aversion appears to be driven by reluctance to act in situations in which a person feels comparatively ignorant predicting outcomes (Heath and Tversky, 1991), and such preferences tend to diminish or disappear in the absence of a direct comparison between more and less familiar events or with more or less knowledgeable individuals (Fox and Tversky, 1995; Chow and Sarin, 2001; Fox and Weber, 2002). For a discussion of how source preferences can be incorporated into the two-stage model see Fox and Tversky (1998); for a more detailed account of "source functions" in a prospect theory framework see Abdellaoui *et al*. (2011a).

### Decisions from Experience

In the standard decision under risk paradigm, a decision maker is presented with outcomes that occur with probabilities that are either transparent (e.g., win \$100 if a fair coin lands heads) or explicitly described (e.g., win \$100 with probability .5). In situations where people learn probability distributions over possible outcomes by sampling from these distributions (as in the *Iowa Gambling Task* or *Balloon Analogue Risk Task*), a straightforward application of prospect theory may not apply, a point developed in Chapter 9. Notably, Hertwig and colleagues (2004) developed a *decision from experience* paradigm in which participants sample from different prospects (i.e., different probability distributions over possible outcomes) as many times as they like before choosing between them, observing choice patterns that appear at first glance to diverge from prospect theory. This has given rise to a robust literature on the putative *description-experience gap* (for reviews, see Hertwig and Erev, 2009; Hertwig, 2012). Researchers wishing to study prospect theory using paradigms in which participants learn probability distributions through sampled experience would be well-advised to pay close attention to this developing literature.

In general, at least three complications can arise when employing a sampling paradigm to investigate prospect theory-like behavior: (1) sampled probabilities do not necessarily coincide with objective probabilities; (2) subjective beliefs do not necessarily coincide with sampled experience; (3) probability weighting may be less distorted when outcomes are experienced rather than described. Below we briefly elaborate on each of these points.

First, a property of the binomial distribution[8] is that very rare events are generally more likely to be undersampled than over-sampled and the opposite is true for very common events. To illustrate, imagine a situation in which a decision maker samples outcomes from two decks of cards: the first deck offers a .05 chance of $100 (and nothing otherwise) while the second deck offers $5 for sure. If decision makers sample a dozen cards from each deck, most of them will never sample $100 from the first deck and therefore face an apparent choice between $0 for sure and $5 for sure, and therefore forgo the 5% chance of $100, contrary to the pattern typically observed in decision under risk (see Table A.2A). (For further discussion of these issues see Hertwig *et al*., 2004 and Fox and Hadar, 2006). Of course, this problem can be solved by ensuring that participants sample from a distribution exhaustively and without replacement so that the sampled distribution matches the objective probability distribution over outcomes.

Second, subjective beliefs of participants may not coincide with sampled experience. For instance, a participant who samples distribution *A* that offers $4 with probability .8 and distribution *B* that offers $3 with certainty may favor a draw from distribution *A* (contrary to the modal prospect theory response that underweights a high probability relative to certainty) because she treats distribution *B* as uncertain as well. Such an intuition may be especially strong, if prior trials have involved two distributions with both zero and nonzero outcomes (Hadar and Fox, 2009). This problem may be solved by making it abundantly clear to participants that they have sampled the complete probability distribution over all possible outcomes. Nevertheless, participants in some experiments may have an imperfect memory for the outcomes they have sampled. For instance, they may afford greater weight to more recently sampled outcomes (Hertwig *et al*., 2004), or they may treat streaks of sampled outcomes as self-correcting (i.e., the *gambler's fallacy*) or self-perpetuating (i.e., believe they have a "hot hand"; see, e.g., Ayton and Fischer, 2004).

Third, it appears that even when participants' experience coincides with objective probability distributions that they are forced to sample exhaustively without replacement, their decisions from experience may diverge from decisions from description (Ungemach *et al*., 2009). In a series of studies Fox and colleagues (2013) replicate the persistence of this description−experience gap, and find that the data fit a prospect theory model with linear decision weighting in decisions from sampled experience (outcomes were weighted by their respective probabilities). Likewise, Hilbig and Glöckner (2011) find evidence consistent with linear probability weighting using an "open sampling" paradigm in which participants view a matrix of possible outcomes presented in proportion to their respective probabilities. Fox and colleagues (2013) argue that sampling forces participants to allocate attention over possible outcomes in proportion to their respective probabilities, whereas describing probabilities of possible outcomes allows participants to allocate attention more equally so that they overweight low probabilities and underweight high probabilities.[9]

## Challenges to Prospect Theory

While prospect theory has been the most successful descriptive model of decision under risk yet advanced, there have been a few noteworthy challenges to its descriptive validity. Researchers interested in how the brain processes decisions under risk should attend closely to these challenges because they also suggest possible alternative processes on which people may rely to make such decisions (for more discussion on alternative models of risky choice, see Chapter 3). We highlight three noteworthy challenges here.

### *Violations of Coalescing and Configural Weighting Models*

Birnbaum (2008) recently reviewed several paradoxes that challenges predictions made by prospect theory. In particular, he examines 11 paradoxes for which prospect theory is not able to correctly predict behavior. One example arises from violations of coalescing. Coalescing means that two branches of a gamble that have the same outcome are treated as one branch with the combined probability. This principle is embedded

[8]The binomial distribution is the discrete probability distribution of the number of successes in a sequence of $n$ independent binary *experiments* (e.g., coin flips), each of which yields success with probability $p$.

[9]Decisions from experience may also exhibit ambiguity aversion. Abdealloui and colleagues (2011c) asked participants to choose between risky prospects sampled using the method of Hertwig and colleagues (2004) and explicitly certain amounts of money. Using this paradigm, they found when making choices involving sampled prospects, participants exhibited similar curvature in the probability weighting function for gains but diminished elevation (and no change in value function parameters).

in the editing rule in original prospect theory and the rank-dependent representation in cumulative prospect theory, respectively. The author discusses experimental findings in which the assumption of coalescing is violated. He argues instead for a class of *configural weighting* models in which people treat gambles not as prospects or probability distributions but as "trees with branches" in which each represented possible outcomes receives a weight. For instance, Birnbaum's *transfer of attention exchange* (TAX) model represents branch weights as reflecting a transfer of attention from branch to branch as a decision maker attends to different possible consequences of a lottery. Branches involving higher probabilities attract more attention, as do branches involving lower outcomes for risk-averse individuals.

### *Heuristic Models*

Expected value maximization, expected utility theory, prospect theory, and even configural weighting models are all examples of *expectation-based models* in which decision makers are assumed to act to maximize some representation of aggregate value of a lottery that is a weighted average of subjective values of possible outcomes. In contrast, heuristic models assume that people make decisions based on a simplified set of rules. In particular, Brandstätter and colleagues (2006) propose the *priority heuristic* that suggests a particular order in which reasons for choosing one prospect over another are examined (minimum gain, probability of minimum gain, maximum gain). The stopping rule states that a decision would be made if the minimum gains differ by one tenth (or more) of the maximum gain. If not, the next reason would be examined from the order set out in the priority rule, that is the probabilities of the minimum gains would be compared. Brandstätter and colleagues (2006) provide evidence suggesting that the priority heuristic can explain many prominent violations of expected utility such as the Allais paradox and the reflection effect, and outperforms cumulative prospect theory in describing some observed choice behaviors. However, in more careful tests Glöckner and Betsch (2008) and Glöckner and Pachur (2012) conclude that cumulative prospect theory better predicts choices than various heuristic rules including the priority heuristic.

### *Violations of Internality and Direct Risk Aversion*

In another challenge to expectation-based models, Gneezy and colleagues (2006) document the *uncertainty effect* in which participants value risky prospects below their worst possible realization. For instance, in one study participants priced a 50−50 chance of receiving either a $50 or else a $100 Barnes and Noble gift certificate lower than another group priced a certainty of receiving a $50 gift certificate. This pattern violates the *internality axiom*, according to which the value of a risky prospect must lie between the values of that prospect's lowest and highest outcomes. It also suggests that decision makers may sometimes respond to risky prospects by discounting their subjective value due to a direct aversion to uncertainty. Research on the uncertainty effect has prompted a lively debate in the literature, with several researchers disputing the generality of the result. For instance, Yang and colleagues (2012) provide evidence suggesting the effect may be artifact of the way in which prospects are described (e.g., as "lotteries" versus "gift certificates").

## PROSPECT THEORY MEASUREMENT

Several applications of prospect theory — from neuroeconomics to decision analysis to behavioral finance — require individual assessment of value and weighting functions. In order to measure the shape of the value and weighting function exhibited by participants in the laboratory, we must first discuss how these functions can be formally modeled. We next discuss procedures for eliciting values and decision weights.

### Parameterization

It is important to note that in prospect theory *value* and *weighting functions* are characterized by their qualitative properties rather than particular functional forms. It is often convenient, however, to fit data to equations that satisfy these qualitative properties. A survey of parameterizations of prospect theory's value and weighting functions can be found in Stott (2006). We review below the functional forms that have received the most attention in the literature to date.

### *Value Function*

The value function is assumed to be concave for gains, convex for losses, and steeper for losses than for gains. By far the most popular parameterization, advanced by Tversky and Kahneman (1992) relies on a power function:

$$\text{(V1)} \qquad v(x) = \begin{cases} x^{\alpha} & x \geq 0 \\ -\lambda(-x)^{\beta} & x < 0 \end{cases} \tag{A.10}$$

where $\alpha$, $\beta > 0$ measure the curvature of the value function for gains and losses, respectively, and $\lambda$ is the coefficient of loss aversion. Thus, the value function for gains (losses) is increasingly concave (convex) for smaller values of $\alpha$ ($\beta$) $< 1$, and loss aversion is more pronounced for larger values of $\lambda > 1$. Tversky and Kahneman (1992) estimated median values of $\alpha = 0.88$, $\beta = 0.88$, and $\lambda = 2.25$ among their sample of college students. In prospect theory, the power function is equivalent to *preference homotheticity:* as the stakes of a prospect $(x, p)$ are multiplied by a constant $k$ then so is the certainty equivalent of that prospect, $c(x, p)$ so that $c(kx, p) = kc(x, p)$ (see, e.g., Tversky, 1967). Empirically, this assumption tends to hold up only within an order of magnitude or so, and as the stakes of gambles increase by orders of magnitude, risk aversion tends to increase for gains — especially when the stakes are real (Holt and Laury, 2002), although the evidence for losses is mixed (Fehr-Duda *et al*., 2010). Thus, for example, a person who is indifferent between \$3 and (\$10, .5) will tend to strictly prefer \$30 over (\$100, .5). Nevertheless, most applications of prospect theory have assumed a power value function.[10] Other common functional forms include the logarithmic function $v(x) = \ln(\alpha + x)$, originally proposed by Bernoulli (1738), which captures the notion that marginal utility is proportional to wealth, and quadratic $v(x) = \alpha x - x^2$, which can be reformulated in terms of a prospect's mean and variance, which is convenient in finance models (For a discussion of additional forms including exponential and expo-power, see Chapter 9 or Abdellaoui *et al*., 2007a).

Surprisingly, there is no canonical definition or associated measure of loss aversion, though several have been proposed. First, in the original formulation of prospect theory (Kahneman and Tversky, 1979) loss aversion was defined as the tendency for the negative value of losses to be larger than the value of corresponding gains (i.e., $-v(-x) > v(x)$ for all $x > 0$) so that a coefficient of loss aversion might be defined, for example, by the mean or median value of $-v(-x)/v(x)$ over a particular range of $x$. Second, the aforementioned parameterization (V1) from Tversky and Kahneman (1992) that assumes a power value function implicitly defines the loss aversion as the ratio of value of losing a dollar to gaining a dollar (i.e., $-v(-\$1) > v(\$1)$) so that the coefficient is defined by $-v(-\$1)/v(\$1)$. Third, Wakker and Tversky (1993) defined loss aversion as the requirement that the slope of the value function for any amount lost is larger than the slope of the value function for the corresponding amount gained (i.e., $v'(-x) > v'(x)$) so that the coefficient can be defined by the mean or median value of $v'(-x)/v'(x)$. Fourth, Köbberling and Wakker (2005) pointed to the kink at the origin so that the coefficient can be defined as the ratio of slope of $v(x)$ as measured from below $x = 0$ to above $x = 0$. Note that if one assumes a simplified value function that is piecewise linear (as in Tom *et al*., 2007), then all four of these definitions coincide. For a fuller discussion see Abdellaoui *et al*. (2007b).

### *Weighting Function*

In fitting their data Tversky and Kahneman (1992) introduced a single-parameter weighting function:

$$\text{(W1)} \qquad w(p) = \frac{p^\gamma}{(p^\gamma + (1-p)^\gamma)^{1/\gamma}} \qquad \text{(A.11)}$$

This form is inverse-S shaped, with overweighting of low probabilities and underweighting of moderate to high probabilities for values of $\gamma < 1$. This function is plotted for various values of $\gamma$ in Figure A.3A.

Probably the most popular form of the weighting function, due to Lattimore and colleagues (1992; see also Goldstein and Einhorn, 1987), assumes that the relation between $w$ and $p$ is linear in a log-odds metric:

$$\text{(W2)} \qquad w(p) = \frac{\delta p^\gamma}{\delta p^\gamma + (1-p)^\gamma} \qquad \text{(A.12)}$$

where $\delta > 0$ measures the elevation of the weigthing function and $\gamma > 0$ measures its degree of curvature. The weighting function is more elevated (exhibiting less overall risk aversion for gains, more overall risk aversion for losses) as $\delta$ increases and more curved (exhibiting more rapidly diminishing sensitivity to probabilities around the boundaries of 0 and 1) as $\gamma < 1$ decreases (the function exhibits an S-shaped pattern that is more pronounced for larger values of $\gamma > 1$).[11] Typically the decision weights of complementary events sum to less than one ($w(p) + w(1 - \mathrm{p}) < 1$), a property known as *subcertainty* (Kahneman and Tversky, 1979). This property is satisfied whenever $\delta < 1$. The Lattimore and colleagues (1992) function is plotted for various values of the elevation parameter $\delta$ and curvature parameter $\gamma$ in Figures A.3B and A.3C, respectively.

Prelec (1998; also Prelec, 2000) derived a functional form of the weighting function that accommodates three principles: (1) overweighting of low probabilities and underweighting of high probabilities; (2) subproportionality of decision weights (a condition that derives from the common ratio effect, Decisions 1 and 2 above); (3) subadditivity of decision weights (a condition that derives from the common consequence effect, Decisions 3 and 4 above). These three principles are all subsumed by a single axiom called

[10]This may be justified in light of recent evidence suggesting that increasing relative risk aversion for gains is largely attributable to variation in the weighting function rather than the value function (Fehr-Duda *et al*., 2010).

[11]For more on elevation versus curvature of the probability weighting function and a preference foundation for a two-parameter family of weighting functions, see Abdellaoui *et al*. (2010).

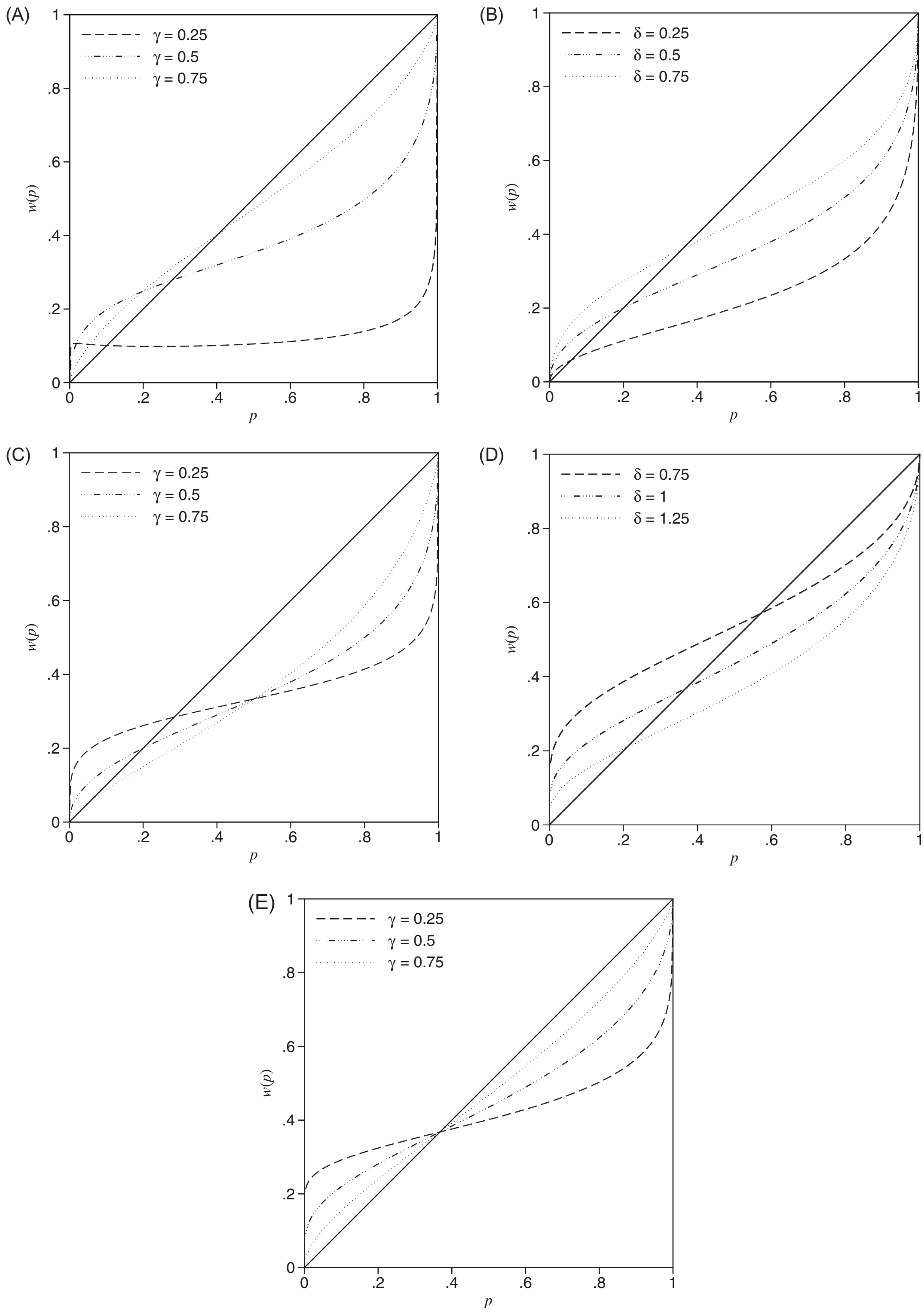


FIGURE A.3 Most common parametric forms used for modeling the probability weighting function from prospect theory. (A) Tversky and Kahneman's (1992) function (W1) for various values of $\gamma$. (B) Lattimore and colleagues' (1992) function for various values of $\delta$ assuming $\gamma = 0.5$ (W2). (C) Lattimore and colleagues' (1992) function for various values of $\gamma$ assuming $\delta = 0.5$ (W2). (D) Prelec's (1998) two-parameter function for various values of $\delta$ assuming $\gamma = 0.5$ (W3A). (E) Prelec's (1998) function for various values of $\gamma$ assuming $\delta = 1$, which results in a single-paramter version of the Prelec function (W3B).

*compound invariance*[12] which implies the following functional form of the weighting function:

$$\text{(W3A)} \qquad w(p) = \exp[-\delta(-\ln p)^{\gamma}], \qquad \text{(A.13)}$$

where $\delta, \gamma > 0$. Note that when $\delta = 1$, Prelec's function collapses to a single-parameter form:

$$\text{(W3B)} \qquad w(p) = \exp[-(-\ln p)^{\gamma}], \qquad \text{(A.14)}$$

which implies a weighting function that crosses the identity at $1/e$. Prelec's two-parameter function is plotted for various values of the elevation parameter $\delta$ in Figure A.3D, and the one-parameter function (i.e., $\delta = 1$) is plotted for various values of the curvature parameter $\gamma$ in Figure A.3E.

The prospect theory value and weighting function parameters can all be estimated for individuals using simple choice tasks. Table A.3 presents measured parameters for monetary gambles from several laboratory and online studies that have assumed a power value function and various weighting functions described above.[13]

Although the typical measured values of these parameters suggest an S-shaped value function ($0 < \alpha < 1$; $0 < \beta < 1$) with loss aversion ($\lambda > 1$), and an inverse-S shaped weighting function that crosses the identity line below .5, there is considerable heterogeneity between individuals in these measured parameters. For instance, in a sample of 10 psychology graduate students evaluating gambles involving only the possibility of gains, Gonzalez and Wu (1999) obtained measures of $\alpha$ in the range from 0.23 to 0.68 (V1), $\delta$ in the range from 0.21 to 1.51, and $\gamma$ in the range from 0.15 to 0.89 (W2).

As a practical matter, although the two-parameter functions (W2) and (W3) have different axiomatic implications, they are difficult to distinguish empirically in the normal range (i.e., .01 to .99) of probabilities (see Gonzalez and Wu, 1999). For the remainder of the chapter, we will refer to the parameters from the Lattimore *et al*. (1992) function (W2).

### *Interaction of V(·) and W(·)*

As mentioned above, prospect theory value and weighting functions both contribute to observed risk attitudes: concavity (convexity) of the value function contributes to risk aversion (seeking) for pure gain (loss) prospects that is reinforced by underweighting of moderate to high probabilities and is reversed by overweighting of low probabilities; loss aversion contributes to risk aversion for mixed prospects. Note that outcome valuation and probability weighting appear to contribute independently to risk preference: recent empirical work suggests that value and weighting function parameters are not strongly correlated (Qui and Steiger, 2011; but see also Toubia *et al*., 2013).

To see more clearly how the value and weighting functions interact, consider the simple case of a prospect $(x, p)$ that offers $x with probability $p$ (and nothing otherwise). Let $c(x, p)$ be the certainty equivalent of $(x, p)$, that is, the sure amount that a person finds equally attractive to the prospect. For instance, a decision maker for whom $c(100, .5) = 30$ is indifferent between receiving $30 for sure or a 50–50 chance of $100 or nothing. Thus, this decision maker would strictly prefer the prospect to $29 and would strictly prefer $31 to the prospect. If we elicit certainty equivalents for a number of prospects in which we hold $x$ constant and vary $p$, then we can derive a plot of *normalized certainty equivalents*, $c/x$ as a function of probability. Such a plot can be instructive, because it indicates probabilities (of two-outcome gambles) for which the decision maker is risk seeking ($c/x > p$), risk neutral ($c/x = p$) and risk averse ($c/x < p$) by whether the curve lies above, on, or below the identity line, respectively.

To see how $w(\cdot)$ and $v(\cdot)$ jointly contribute to risk attitudes, note that, under prospect theory, $V(c) = V(x,p)$, so that $v(c) = w(p)v(x)$ or $w(p) = v(c)/v(x)$. Assuming the power value function (V1), we get $w(p) = (c/x)^{\alpha}$, or

$$c/x = w(p)^{1/\alpha} \qquad \text{(A.15)}$$

In the case of gains, normalized certainty equivalents will increase with the parameter $\alpha$, and assuming a typical concave value function ($\alpha < 1$), they will be lower than corresponding decision weights. These observations give rise to two important implications. First, overweighting of low probabilities does not necessarily translate into risk seeking for low probability gains. To illustrate, consider the weighting function obtained from the median data of Gonzalez and Wu (1999), assuming the Lattimore and colleagues (1992) function (W2), with $\delta = 0.77$, $\gamma = 0.44$, which illustrates considerable overweighting of low probabilities; for example, $w(.05) = .17$. In that study the authors obtained $\alpha$ in the range from 0.68 (moderate concavity) to 0.23 (extreme

[12]Defined as: for any outcomes $x$, $y$, $x'$, $y'$, probabilities $q$, $p$, $r$, $s$, and the compounding integer $N \geq 1$, if $(x,p) \sim (y,q)$ and $(x,r) \sim (y,s)$ then $(x',p^N) \sim (y',q^N)$ implies $(x',r^N) \sim (y',s^N)$.

[13]It is an open question in what ways measured parameters vary across populations and settings. For instance, in one recent field study, prospect theory parameters fitted to US stock option prices were somewhat more linear (i.e., closer to expected value maximization) than typical laboratory studies have implied (Gurevich *et al*., 2009).

TABLE A.3 Measured Prospect Theory Parameters from Several Studies

(V1) $v(x) = \begin{cases} x^{\alpha} & x \geq 0 \\ -\lambda(-x)^{\beta} & x < 0 \end{cases}$

| Study | $n$ | Population | IC | ET | $\alpha$ | $\beta$ | $\lambda$ |
|---|---|---|---|---|---|---|---|
| Tversky and Kahneman (1992) | 25 | Graduate students | f | mie | 0.88 | 0.88 | 2.25 |
| Camerer and Ho (1994) | – | Meta-analysis of nine studies | – | – | 0.23 | | |
| Wu and Gonzalez (1996) | 420 | Undergraduate students | f | pool | 0.49 | | |
| Gonzalez and Wu (1999) | 10 | Graduate students (psychology) | g | med | 0.49 | | |
| Abdellaoui (2000) | 46 | University students (economics) | g | med | 0.89 | 0.92 | |
| Etchart-Vincent (2004) | 35 | University students (economics) | f | mie | | 0.97 | |
| Abdellaoui *et al.* (2005) | 41 | Graduate students (business) | f | mie | 0.91 | 0.96 | |
| Stott (2006) | 96 | University students | g | mie | 0.19 | | |
| Abdellaoui *et al.* (2007b) | 48 | University students (economics) | f | mie | 0.72 | 0.73 | 1.69 |
| Abdellaoui *et al.* (2008) | 48 | Graduate students (econ. and math.) | g | mie | 0.86 | 1.06 | 2.61 |
| Rieskamp (2008) | 30 | University students | b | mie | 0.93 | 0.89 | 1.00 |
| Harrison and Rutström (2009) | 158 | University students (business) | b | mie | 0.71 | 0.72 | 1.38 |
| Booij *et al.* (2010) | 1935 | General public | f | pool | 0.86 | 0.83 | 1.58 |
| Bruhin *et al.* (2010) | 448 | University students | b | mie | 0.94 | 1.14 | |
| Tanaka *et al.* (2010) | 181 | Vietnamese villagers | b | mnie | 0.61 | $=\alpha$ | 2.63 |
| Abdellaoui *et al.* (2011b) | 52 | Undergraduate students (economics) | g | mie | 0.86 | | |
| Abdealloui *et al.* (2011c) | 61 | Undergraduate students (business) | g | mie | 0.79 | 0.96 | 2.47 |
| Glöckner and Pachur (2012) | 66 | University students | b | mie | 0.74 | $=\alpha$ | 1.16 |
| Zeisberger *et al.* (2012) | 86 | Undergraduate students | b | mie | 1.00 | 0.91 | 1.42 |
| Abdellaoui *et al.* (2013a) | 46 | Financial professionals | f | mie | 0.73 | 0.86 | 1.31 |
| Erner *et al.* (2013) | 148 | University students (business) | f | mie | 1.15 | 0.93 | 2.51 |
| Toubia *et al.* (2013) | 137 | Amazon Mechanical Turk | b | mie | 0.46 | $=\alpha$ | 1.78 |
| Vrecko and Langer (2013) | 202 | Undergraduate students | b | mie | 1.19 | 0.98 | 1.39 |

(W1) $w(p) = \dfrac{p^{\gamma}}{(p^{\gamma}+(1-p)^{\gamma})^{\frac{1}{\gamma}}}$

| Study | $n$ | Population | IC | ET | $\gamma^{+}$ | $\gamma^{-}$ |
|---|---|---|---|---|---|---|
| Tversky and Kahneman (1992) | 25 | Graduate students | f | mie | 0.61 | 0.69 |
| Camerer and Ho (1994) | – | Meta-analysis of nine studies | – | – | 0.56 | |
| Wu and Gonzalez (1996) | 420 | Undergraduate students | f | pool | 0.71 | |
| Abdellaoui (2000) | 46 | University students (economics) | g | med | 0.60 | 0.70 |
| Stott (2006) | 96 | University students | g | mie | 0.96 | |
| Rieskamp (2008) | 30 | University students | b | mie | 0.77 | 0.76 |
| Harrison and Rutström (2009) | 158 | University students (business) | b | mie | 0.91 | 0.91 |
| Glöckner and Pachur (2012) | 66 | University students | b | mie | 0.61 | 0.89 |
| Zeisberger *et al.* (2012) | 86 | Undergraduate students | b | mie | 0.86 | 0.82 |
| Vrecko and Langer (2013) | 202 | Undergraduate students | b | mie | 0.72 | 0.63 |

(*Continued*)

TABLE A.3 (Continued)

| (W2) $w(p) = \frac{\delta p^{\gamma}}{\delta p^{\gamma} + (1-p)^{\gamma}}$ | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Study** | ***n*** | **Population** | **IC** | **ET** | $\gamma^+$ | $\delta^+$ | $\gamma^-$ | $\delta^-$ |
| Tversky and Fox (1995) | 40 | University students (football fans) | f | med | 0.69 | 0.77 | | |
| Wu and Gonzalez (1996) | 420 | Undergraduate students | f | pool | 0.68 | 0.84 | | |
| Gonzalez and Wu (1999) | 10 | Graduate students (psychology) | g | med | 0.44 | 0.77 | | |
| Abdellaoui (2000) | 46 | University students (economics) | g | med | 0.60 | 0.65 | 0.65 | 0.84 |
| Abdellaoui *et al.* (2005) | 41 | Graduate students (business) | f | med | 0.83 | 0.98 | 0.84 | 1.35 |
| Stott (2006) | 96 | University students | g | mie | 0.96 | 1.40 | | |
| Booij *et al.* (2010) | 1935 | General public | f | pool | 0.62 | 0.77 | 0.59 | 1.02 |
| Bruhin *et al.* (2010) | 448 | University students | b | mie | 0.38 | 0.93 | 0.40 | 0.99 |
| Abdealloui *et al.* (2011c) | 61 | Undergraduate students (business) | b | mie | 0.65 | 0.70 | 0.73 | 0.78 |
| Glöckner and Pachur (2012) | 66 | University students | b | mie | 0.67 | 0.63 | 0.81 | 1.87 |
| Erner *et al.* (2013) | 148 | University students (business) | f | mie | 0.93 | 0.75 | 0.87 | 1.10 |
| **(W3A)** $w(p) = e^{-\delta(-ln(p))^{\gamma}}$ | | | | | | | | |
| **Study** | ***n*** | **Population** | **IC** | **ET** | $\gamma^+$ | $\delta^+$ | $\gamma^-$ | $\delta^-$ |
| Stott (2006) | 96 | University students | g | mie | 1.00 | 1.00 | | |
| Abdellaoui *et al.* (2011b) | 52 | Undergraduate students (econ.) | g | mie | 0.62 | 1.20 | | |
| van de Kuilen and Wakker (2011) | 78 | Undergraduate students | g | mie | 1.15 | 1.58 | | |
| **(W3B)** $w(p) = e^{-(-ln(p))^{\gamma}}$ | | | | | | | | |
| **Study** | ***n*** | **Population** | **IC** | **ET** | $\gamma^+$ | $\gamma^-$ | | |
| Wu and Gonzalez (1996) | 420 | Undergraduate students | f | pool | 0.74 | | | |
| Stott (2006) | 96 | University students | g | mie | 0.94 | | | |
| Tanaka *et al.* (2010) | 181 | Vietnamese villagers | b | mnie | 0.74 | | | |
| Toubia *et al.* (2013) | 137 | Amazon Mechanical Turk | g | mie | 0.53 | | | |

This table lists parameter estimates taken from several studies. The column labeled "IC" refers to the incentive compatible payment with "f" fixed (noncontingent) payment, "g" variable (contingent) payment for gains only, and "b" variable payment for both gains and losses. The column labeled "ET" refers to the estimation type with "mie" medians of individual estimates, "mnie" means of individual estimates, "med" estimates using median data, and "pool" estimates using pooled data. In cases where both the estimates using median data as well as the medians of individual estimates were reported, only the medians of the individual estimates are listed. Criteria for inclusion were monetary prospects, decisions under risk, and estimates obtained using the power value function. In some cases, parameters are averaged across conditions or only selected conditions are reported. "$=\alpha$" indicates that one common curvature parameter was fitted for both gains and losses. Definitions of loss aversion vary across studies (see Abdellaoui *et al.*, 2007b).

concavity) for their 10 participants. Using these extreme values, we obtain wildly different $c/x$ functions as depicted in Figure A.4. For instance, given these values $c(100, .05) = 7.65$ and 0.05, respectively, indicating moderate risk seeking and extreme risk-aversion, respectively.

Second, the interaction of value and weighting functions makes it difficult to empirically distinguish variations in the measured elevation of the weighting function from variations in the measured curvature of the value function. For instance, when $\alpha = 0.68$, $\delta = 0.77$, and $\gamma = 0.44$ we get $c(100, .5) = 29.40$. A virtually identical certainty equivalent follows assuming, for example, $\alpha = 0.88$, $\delta = 0.52$, and $\gamma = 0.44$. Both of these normalized certainty equivalent functions are illustrated in Figure A.5. Thus, if one is concerned with parsing the contribution of subjective value versus probability weighting on observed risk attitudes, one must elicit the value and weighting functions with care. For instance, if one assumes a single-parameter weighting function (e.g., (W1) or

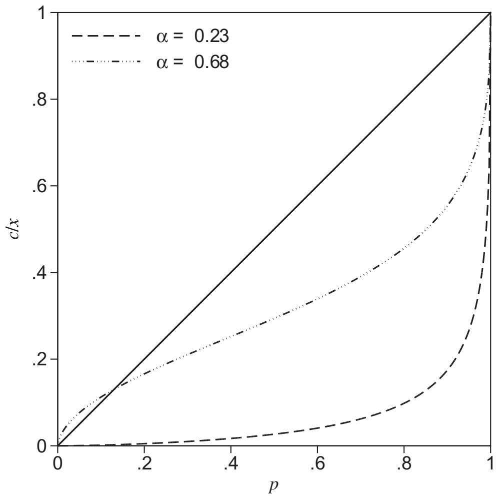


FIGURE A.4 Normalized certainty equivalents as a function of probability assuming the Lattimore and colleagues (1992) weighting function, with $\delta = 0.77$ and $\gamma = 0.44$ (median values from Gonzalez and Wu, 1999) and assuming a power value function, with $\alpha = 0.23$ and 0.68 (the range obtained from participants of Gonzalez and Wu, 1999). This figure illustrates the interaction of the value and weighting functions in determining risk attitudes.

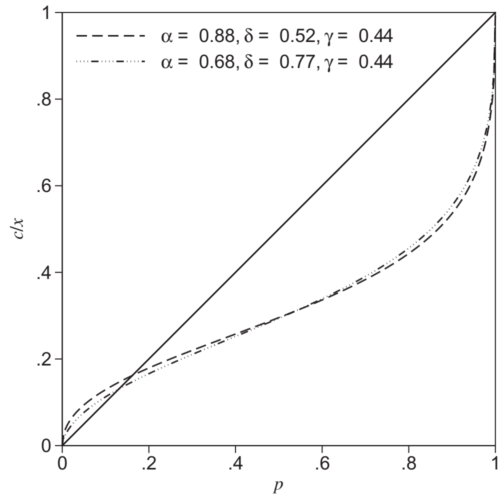


FIGURE A.5 Normalized certainty equivalents as a function of probability assuming the Lattimore and colleagues (1992) weighting function and power value function with $\alpha = 0.68$, $\delta = 0.77$, and $\gamma = 0.44$ versus $\alpha = 0.88$, $\delta = 0.52$, and $\gamma = 0.44$. This figure illustrates the difficulty empirically distinguishing between elevation of the weighting function and curvature of the value function.

(W3B)) when "true" weighting functions vary in their elevation, one may obtain incorrect measures. A researcher may believe that a particular pattern of neural activity covaries with curvature of the value function, when in fact it covaries with elevation of the weighting function.[14]

## Elicitation

Several methods have been proposed for eliciting value and weighting function parameters. Broadly speaking these methods fall into four categories:

1. A statistical method that estimates $v(x_i)$ and $w(p_i)$ from a participant's certainty equivalents for prospects that factorially combine each $x_i$ and $p_i$.
2. Nonparametric methods that separately assess values then assess decision weights, making no assumptions concerning the functional form of the value and weighting functions.
3. Semiparametric methods that assume a functional form for the value or weighting function and assess the other function nonparametrically.
4. Parametric methods that assume a functional form of both the value and weighting function.

The first three approaches allow for direct estimation of values of specific dollar outcomes and/or weights of specific probabilities, which can be subsequently fit to various parametric forms. The fourth approach fits parameters directly to choice or pricing data. We will review each of the most noteworthy methods in turn then evaluate their respective strengths and weaknesses.

### *Statistical Method: Gonzalez and Wu (1999)*

Perhaps the most careful elicitation of prospect theory value and weighting functions to date was advanced by Gonzalez and Wu (1999). Ten graduate students in Psychology from the University of Washington were paid $50 plus an incentive-compatible payment (contingent on their choices) for their

[14]Similarly, misspecification of the curvature of the value function can perturb measurement of loss aversion. For instance, if one assumes that the value function for gains and losses are identical when in fact the value function is more concave for gains than losses, then one will generally overestimate the degree of loss aversion (see Nilsson *et al*., 2011).

participation in four 1-hour sessions.[15] Participants were presented with 15 two-outcome (non-negative) gambles crossed with 11 probabilities (=165 gambles), presented in a random order.

Certainty equivalents were assessed for each gamble through a series of choices. For instance, consider the prospect that offered a 50−50 chance of \$100 or nothing. A participant was asked if he preferred to receive the prospect or various sure amounts that ranged from \$100 to \$0 in increments of \$20. If a participant indicated that he preferred \$40 for sure over the prospect but preferred the prospect over \$20 for sure, then a second round of choices would be presented that spanned this narrower range (from \$40 to \$20). This process was repeated until certainty equivalents could be estimated to the nearest dollar. If, for example, a participant indicated a preference for a sure \$36 over the prospect but a preference for the prospect over a sure \$35, then the researchers estimated $c(100, .5) = 35.5$.

The estimation process used by Gonzalez and Wu (1999) was nonparametric in that it did not make any assumptions concerning the functional form of $v(\cdot)$ or $w(\cdot)$. Their algorithm treated the value of each of the possible outcomes and the weight of each of the probabilities presented as a parameter to be estimated. These parameters were estimated using an alternating least squares procedure in which each step either held $w$ constant and estimated $v$ or held $v$ constant and estimated $w$. The authors assert that this analysis converged on parameter estimates relatively quickly.

The statistical method of Gonzalez and Wu (1999) has several advantages over alternative methods. The elicitation is not very cognitively demanding as participants are merely required to price two-outcome gambles. The procedure gives rise to estimates of values and decision weights that are not distorted by parametric misspecification. On the other hand, the procedure is demanding of participants' time as it requires pricing of a large number of gambles to get stable estimates (the original study required participants to 165 two-outcome gambles, each through a series of several choices). The procedure has not yet been applied to the domain of losses or mixed prospects but such an extension would be straightforward.

### *Nonparametric Methods*

Several other fully nonparametric methods have been advanced for analytically assessing $v(\cdot)$ and $w(\cdot)$. All of them rely on a two-stage process in which $v(\cdot)$ is assessed in a first phase, then applied to the measurement of $w(\cdot)$. The most popular approach to assessing values that makes no assumptions concerning the weighting of probabilities is the *tradeoff method* (Wakker and Deneffe, 1996). The tradeoff method requires participants to make choices between two two-outcome prospects $(x, p; y)$ that offer \$$x$ with probability $p$ otherwise \$$y$, with one of the outcomes adjusted following each choice until indifference between the gambles can be established. Consider a pair of reference outcomes $R > r$, a pair of variable outcomes $x_1 > x_0$, and a fixed probability $p$. On each trial, the values of $R$, $r$, $x_0$, and $p$ are fixed, and $x_1$ is varied until the participant reveals that

$$(x_1, p; r) \sim (x_0, p; R). \tag{A.16}$$

For instance, a participant might be offered a choice between a 50−50 chance of \$100 or \$20 versus a 50−50 chance of \$70 or \$40. If the participant prefers the latter gamble, then the variable payoff of the first gamble (\$100) adjusts to a higher amount (say, \$110). The variable amount can be raised or lowered by decreasing increments until the participant confirms that both prospects are equally attractive. Once indifference is established for this first pair of prospects, the procedure is repeated for a second pair of prospects with the same probability and reference outcomes, but a new variable outcome $x_2 > x_1$, until it is established that:

$$(x_2, p; r) \sim (x_1, p; R). \tag{A.17}$$

According to CPT[16] , the first indifference gives us:

$$v(r)\,[1 - w(p)] + v(x_1)w\big(p\big) = v(R)[1 - w(p)] + v(x_0)w(p),$$

so that

$$w(p)[v(x_1) - v(x_0)] = [1 - w(p)][v(R) - v(r)]$$

and the second indifference gives us

$$v(r)[1 - w(p)] + v(x_2)w(p) = v(R)[1 - w(p)] + v(x_1)w(p),$$

so that

$$w(p)[v(x_2) - v(x_1)] = [1 - w(p)][v(R) - v(r)].$$

Together these indifferences imply equal value intervals as follows:

$$v(x_1) - v(x_0) = v(x_2) - v(x_1).$$

[15]An incentive-compatible payoff is a payment contingent on choice that encourages honest responses by participants. As discussed in Chapter 2, economists are generally skeptical of results of studies that do not include such incentives. In practice, the addition of incentives tends to reduce noise in participant responses and may lead to decreased framing effects and greater risk aversion (for reviews, see Camerer and Hogarth, 1999; Hertwig and Ortmann, 2001).

[16]Assuming $x_0 > R$; this result can be relaxed without affecting the result of the elicitation.

Setting $x_0 = 0$ and $v(x_0) = 0$, we get $v(x_2) = 2v(x_1)$. By eliciting similar yoked indifferences to obtain $x_3$, $x_4$, etc., we can generate a standard sequence of outcomes that are spaced equally in subjective value space, allowing us to construct a parameter-free value function for gains. A similar exercise can be repeated in the measurement of the value function for losses (for an example in the domain of losses, see Fennema and van Assen, 1999).

Once one has obtained a measure of several values from a participant, one can proceed to measure decision weights nonparametrically. Arguably the most popular method, advanced by Abdellaoui (2000), uses the standard sequence of outcomes $x_0, \ldots, x_n$ to elicit a standard series of probabilities $p_1, \ldots, p_{n-1}$ that are equally spaced in terms of their decision weights. This is done by eliciting probabilities such that a mixture of the highest and lowest outcome in the standard sequence is equally attractive to each of the internal outcomes in that sequence. Thus by establishing for each $x_i$ ($i = 1, \ldots, n-1$) the following indifference:

$$(x_n, p_i; x_0) \sim x_i, \tag{A.18}$$

CPT implies:

$$w(p_i) = \frac{v(x_i) - v(x_0)}{v(x_n) - v(x_0)}. \tag{A.19}$$

Because the values of $x_i$ were constructed using the tradeoff method to be equally spaced in terms of their expected value, the above equation reduces to:

$$w(p_i) = i/n. \tag{A.20}$$

An analogous procedure can be followed for losses.

Bleichrodt and Pinto (2000) advance a similar two-step procedure that first relies on the tradeoff method to elicit a standard sequence of outcomes, then elicits decision weights through a matching procedure. Instead of eliciting probabilities that lead to indifference between prospects, their method fixes probabilities and elicits outcomes that match pairs of two-outcome prospects.[17] Such a procedure was used to measure the weighting function for losses by Etchart-Vincent (2004).

More recently, van de Kuilen and Wakker (2011) advanced an ingenious method of measuring decision weights that requires measurement of only a single utility midpoint (i.e., which monetary outcome is half-way between a high outcome and low outcome in terms of its subjective value), using the method of Wakker and Deneffe (1996) described above. The *midweight method* then estimates individual decision weights nonparametrically by allocating probability of obtaining the middle outcome among the high-valued outcome and the low-valued outcome such that the value of the prospect remains unchanged. For instance, if $v(x_1)$ is midway between $v(x_0)$ and $v(x_2)$ and a participant is indifferent between receiving $x_1$ for sure or a probability $p$ of receiving $x_2$ or else receiving $x_0$, then we know that $w(p) = 1/2$ (that is, $w^{-1}(1/2) = p$). Through a series of chained trials, one can continue to bisect decision weights to establish a wide range of inverse decision weights. The midweight method is quite efficient in that it requires a relatively small number of choices to determine a set of decision weights (and only a single utility midpoint). It can also be readily extended from risk to uncertainty. However, it is extremely cognitively demanding because determining decision weights beyond the first midpoint requires participants to choose between pairs of two-outcome prospects whose probabilities also vary. It is also worth noting that, in the first demonstration of this method, van de Kuilen and Wakker (2011) were compelled to drop nearly one-fifth of their respondents who "apparently did not understand the choices or did not think about them seriously" and they obtained a convex shaped weighting function rather than the customary inverse-S (concave then convex) shape.

The aforementioned nonparametric elicitations can be used to assess value and weighting functions separately for gains and losses. Because the value function is a ratio scale (unique to multiplication by a positive constant) a separate procedure using mixed (gain−loss) gambles is required to assess loss aversion. A parameter-free procedure has been advanced by Abdellaoui and colleagues (2007b). Details of the procedure are beyond the scope of this chapter, but the gist is as follows: The first step entails determining through a series of indifferences between prospects the probabilities $p_g$ and $p_l$ for which $w^+(p_g)$ and $w^-(p_l) = 1/2$. This allows determination, in a second stage, of outcome amounts that are midpoints in value space for losses. The third step links value for losses and gains through a series of indifferences that determines a gain outcome that is the mirror image of a loss outcome in value space (i.e., has the same absolute value of utility/value). Finally, the fourth step repeats the second step by determining outcomes that are midpoints in value space for gains. The method of Abdellaoui and colleagues (2007b) is mathematically elegant and yields clean results consistent with prospect theory in the analysis of aggregate data from a sample of 48 economics students.

[17]Because the new outcomes may not be included in the standard sequence, this method requires an interpolation procedure and thus is not fully nonparametric.

It can also be readily extended to the measurement of the weighting function by merely eliciting probability equivalences (Blavatskyy, 2006).[18] However, the task is cognitively demanding, as it relies on choices between pairs of two-outcome gambles to determine the crucial values of probabilities that are weighted at one-half (step one), and it is laborious, as it entails a complex four-step procedure with disparate response modes.

Nonparametric methods tend to be less time consuming than statistical methods of elicitation. Also, unlike semiparametric and fully parametric methods, they make no assumptions concerning the functional form of the value and weighting functions that might distort measurement, though functions can be fit to the measured values and weights that are obtained. Moreover, nonparametric methods preserve a direct link between specific choices and measured utilities so that specific inconsistencies can be traced to particular choices. Unfortunately, nonparametric methods are generally quite cognitively demanding, requiring choices between multiple two-outcome prospects (or even more complicated choices). Thus, these methods may not give utterly robust measurements as participants may fall back on decision heuristics (such as expected value maximization) or respond in an inconsistent manner. Moreover, because these methods generally rely on elicitation of a standard sequence of values using the tradeoff method, there is the possibility that error in measuring the first step in the sequence will be propagated throughout the measurement of values and therefore lead to further error in the measurement of decision weights (however, studies that have investigated error propagation have thus far found no large effect; see Bleichrodt and Pinto, 2000; Abdellaoui *et al*., 2005).

### *Semiparametric Methods*

Semiparametric elicitation methods assume a parametric form of the value function in order to derive nonparametric estimates of decision weights. The simplest semiparametric approach is to assume a power value function, $v(x) = x^{\alpha}$, as fitted to nonparametric measurement of value using the tradeoff method (or assuming representative parameters from previous studies of similar participant populations). Next, decision weights for various probabilities can be determined by eliciting certainty equivalents $c(x, p_i)$ for prospects that pay a fixed amount $x$ with probabilities $p_i$. According to prospect theory, $c(x, p_i)^{\alpha} = w(p_i)x^{\alpha}$. Thus, each decision weight is given by:

$$w(p_i) = [c(x, p_i)/x]^{\alpha}. \tag{A.21}$$

Of course, this method depends on the accuracy of the first-stage measurement of utility.

A more elegant semiparametric method was recently advanced by Abdellaoui and colleagues (2008). This method entails three stages. In the first stage, the value function for gains is elicited and decision weights are measured parameters. This is done by eliciting certainty equivalents $G_i$ for a series of prospects $(x_i, p_g; y_i)$ $(x_i > y_i \geq 0, i = 1, \ldots, k)$. According to CPT:

$$v(G_i) = v(y_i)[1 - w(p_g)] + v(x_i)w(p_g). \tag{A.22}$$

Define $w(p_g) \equiv \omega^+$ and assume a power value function $v(x) = x^{\alpha}$. We get:

$$G_i = (\omega^+(x_i^{\alpha} - y_i^{\alpha}) + y_i^{\alpha})^{1/\alpha}. \tag{A.23}$$

Thus, by varying $x_i$ and $y_i$ and measuring certainty equivalents $G_i$, the parameters $\omega^+$ and $\alpha$ can be estimated using non-linear regression. An analogous method can be used in a second stage for the domain of losses to measure decision weight and power value function parameters $\omega^-$ and $\beta$. Finally, a third stage links the value function for gains and losses by selecting a gain amount $G^*$ within the range of values measured in step one, then determining the loss amount $L^*$ such that a participant finds the mixed prospect $(G^*, p_g; L^*)$ barely acceptable (i.e., is indifferent to playing the prospect or not). This implies that:

$$\omega^+ v(G^*) + \omega^- \lambda v(L^*) = v(0) = 0, \tag{A.24}$$

so that one can easily solve for $\lambda$. Although the method of Abdellaoui and colleagues (2008) is designed to elicit value function and loss aversion parameters, it also provides as a byproduct measurement of a decision weight. By repeating the procedure for various probabilities of gain and loss, several decision weights can be obtained for mapping (or fitting parameters to) more complete weighting functions.

Semiparametric methods provide a compromise between accuracy of a nonparametric elicitation method and the efficiency of a parametric method. They tend to be less cognitively demanding and less

[18] That is, the probability $p$ of receiving outcome $x_2$ otherwise $x_0$ that makes it equally attractive to receiving $x_1$ for sure, where $v(x_2) > v(x_1) > v(x_0)$ are all determined in the first four stages.

time consuming than pure nonparametric methods and the statistical method.

### Parametric Methods

The final approach to eliciting prospect theory value and weighting functions is a purely parametric approach in which functional forms for the value and weighting function are fitted directly to choice and/or pricing data. This fitting can be done using a variety of statistical techniques, from regression to maximum likelihood estimation (e.g., Stott, 2006) to hierarchical Bayesian modeling (e.g., Nilsson *et al*., 2011).

Tversky and Kahneman (1992) elicited certainty equivalents for a number of single- and two-outcome prospects entailing pure gains, pure losses, and mixed outcomes. These were entered into a non-linear regression assuming a power value function (V1) and single-parameter weighting function.

A simpler procedure can be executed using Prelec's (1998) single-parameter weighting function (W3B) and a power value function. If we elicit a number of certainty equivalents $c_{ij}$ for prospects that pay $\$x_i$ with probability $p_j$, then we get by prospect theory:

$$c_{ij}^{\alpha} = x_i^{\alpha}\exp[-(\ln p)^{\gamma}]. \tag{A.25}$$

Collecting outcomes on the left side of the equation and taking the double log of both sides, we get:

$$-\ln[-\ln(c_{ij}/x_i)] = \ln(\alpha) + \gamma[-\ln(-\ln p_j)]. \tag{A.26}$$

This equation lends itself to linear regression to determine the parameters $\alpha$ and $\gamma$.

A simple parametric method for measuring loss aversion was introduced by Tom and colleagues (2007). This method merely requires participants to make a series of choices whether or not to accept mixed prospects that offered a 50−50 chance of gaining $\$x$ or losing $\$y$ in which $x$ and $y$ were independently varied. If one assumes a piecewise linear[19] value function (and also $w^{+}(.5) = w^{-}(.5)$), weight afforded to gains and losses can be determined through logistic regression. This method has the unique advantage of allowing separate measurement of sensitivity to gains and losses (the regression coefficients), as well as overall bias to accept or reject gambles (the intercept term).

Most elicitation procedures discussed thus far are somewhat time-consuming and laborious which makes it difficult to apply them outside the lab or when there are severe time constraints in elicitation. Two new methods have emerged that provide highly efficient measurement of prospect theory parameters (though at the cost of lower resolution or reliability of measurement). In the first, Tanaka and colleagues (2010) presented participants with three series of paired lotteries. For each series, participants were asked to indicate their switching point; that is, the gamble pair where they would switch preference from option A to option B. Each combination of the three switching points is associated with a particular interval for each of the three preference parameters (curvature, probability weighting, loss aversion). This method is analogous to a popular method for eliciting risk aversion parameters in an expected utility context (Holt and Laury, 2002). It can be executed in only a few minutes but yields parameter estimates that are highly coarse.

In the second, Toubia *et al.* (2013) developed an adaptive design in which the sequence of choice problems presented to participants is optimized to maximize the information content that can be derived from each choice problem. The information content is measured in a Bayesian framework, which allows determining the optimal branching within a universe of potential choice problems.

Parametric estimation of value and weighting functions has several advantages over other methods. The task of pricing simple prospects is cognitively tractable, the time requirements are relatively modest, and this approach tends to yield reliable measurement. On the other hand, this approach is susceptible to parametric misspecification, particularly if one assumes a single parameter weighting function so that it is difficult to distinguish the curvature of the value function from elevation of the weighting function.

Table A.4 summarizes the major methods of prospect theory elicitation, listing strengths and weaknesses of each method. All entail tradeoffs, and the particular method used by researchers will be determined by the cognitive sophistication of participants, time constraints, and technical constraints of the study methodology in question. Table A.4 assesses cognitive demand in terms of the number of attributes that must be held in working memory when making each choice and/or the number of switches that participants must make between elicitation modes. Thus, the least demanding methods entail assessing whether or not to accept a 50−50 gain−loss prospect or choosing between a two-outcome prospect and a sure thing. The most demanding methods require choosing between prospects with more than two outcomes or choosing between two-outcome prospects that differ in terms of both outcomes and probabilities. The table also

[19]The assumption of linearity is customary and generally a reasonable first approximation, but need not be assumed if one uses alternative statistical techniques for fitting other functional forms to the data. The assumption that the weight of one-half is the same for losses and gains accords reasonably well with the data when it has been carefully tested (see Abdellaoui *et al*., 2008).

**TABLE A.4** Major Prospect Theory Elicitation Methods

| Method Class | Reference | Prospect Theory Component(s) | Cognitive Demand | Time Required |
|---|---|---|---|---|
| Statistical | Gonzalez and Wu (1999) | All | Low | High |
| Nonparametric | Wakker and Deneffe (1996) | $v^+$ or $v^-$ | High | Medium |
| | Abdellaoui *et al*. (2007b) | $v^+$ and $v^-$ | High | Medium |
| | Abdellaoui (2000) | $w^+$ or $w^-$ | High | Medium |
| | Bleichrodt and Pinto (2000) | $w^+$ or $w^-$ | High | Medium |
| | van de Kuilen and Wakker (2011) | $w^+$ or $w^-$ | Very High | Low |
| Semiparametric | Abdellaoui *et al*. (2008) | $v^+$, $w^+$ or $v^-$, $w^-$ | Medium | Medium |
| Parametric | Prelec (1998) | $v^+$, $w^+$ or $v^-$, $w^-$ | Low | Medium |
| | Tom *et al*. (2007) | Loss aversion | Very Low | Medium |
| | Tanaka *et al*. (2010) | $v$, $w$ | Medium | Very Low |
| | Toubia *et al*. (2013) | All | Very High | Very Low |

Methods that allow simultaneous measurement of both $v^+$ and $v^-$ also permit measurement of loss aversion. Methods that measure $v$, $w$ (without superscripts) assume common parameters for losses and gains, also measure loss aversion.

assesses how much time is required for each method in a typical application. Generally speaking *very low* means less than five minutes; *low* means five to 15 minutes; *medium* means 15 minutes to one hour, and *high* means more than one hour.

## Determining Certainty Equivalents

Several elicitation methods discussed above require determination of certainty equivalents of various prospects. The most straightforward (but cognitively demanding) method is to elicit them directly by asking participants for the sure amount of money $c$ that they find equally attractive to a prospect $(x, p)$. Participants can be provided incentives for accuracy using the method described by Becker and colleagues (1964).[20] Alternatively, one might ask participants for the probability $p$ such they find the prospect $(x, p)$ equally attractive to the sure amount $c$. Empirically, such elicitations tend to be noisy, but they are quick and convenient.

We caution researchers against such direct matching procedures. Prospect theory was originally articulated as a model of simple choice between prospects. Direct elicitation of sure amounts or probabilities to match prospects relies on the assumption of *procedure invariance:* two strategically equivalent methods of assessing preference should lead to the identical orderings between prospects. Unfortunately, this assumption is routinely violated. First, people generally afford more weight to payoffs relative to probabilities when they price prospects than when they choose between them. This can give rise to *preference reversal* in which participants price a low-probability high-payoff bet (for example, a 3/36 chance to win $100) above a high-probability low-payoff bet (for example, a 28/36 chance to win $10) even though they prefer the latter to the former when facing a simple choice between them (see, for example, Tversky *et al*., 1990).[21] Second, people tend to be more risk averse when matching prospects by varying probability than when matching prospects by varying outcomes (Hershey and Schoemaker, 1985; see also Bleichrodt *et al*., 2001). For instance, suppose that a participant is asked to report what $p$ of receiving $100 (or else nothing) is equally attractive to receiving $35 for sure, and this participant reports a probability of .5. If that same participant is asked what certain amount is equally attractive to a .5 chance of $100, he will generally report a value greater than $35.

A popular alternative for overcoming limitations of direct matching procedures is to estimate certainty equivalents from a series of choices. For instance in pricing the prospect ($100, .5) that offers a .5 chance of $100, participants can be offered a series of choices

[20]This method is only incentive-compatible if subjects obey the independence axiom (see Chapter 1), which of course is violated in prospect theory. For a further discussion, see Karni and Safra (1987).

[21]For an attempt to accommodate some forms of preference reversal into a version of prospect theory, see Schmidt and colleagues (2008).

between ($100, .5) or $100 for sure, ($100, .5) or $90 for sure, and so forth. For instance, if a participant chooses $40 for sure over ($100, .5) but she also chooses ($100, .5) over $30 for sure, then by linear interpolation we can estimate her certainty equivalent as approximately $35. If a researcher tells participants that a randomly selected choice (from a randomly selected trial) will be honored for real money, then this method will be incentive-compatible (i.e., participants will have an economic incentive to respond honestly).

Sure amounts can be evenly spaced (as in Tversky and Fox, 1995) or logarithmically spaced (as in Tversky and Kahneman, 1992). If a researcher wishes to obtain higher-resolution estimates of certainty equivalents, the sequential choice method cannot be readily accomplished in a single round. One approach is to use an iterated procedure in which a first, coarse evaluation is made followed by a more detailed series of choices, etc. (Tversky and Kahneman, 1992; Tversky and Fox, 1995; Gonzalez and Wu, 1999). For instance, if a participant prefers $40 to ($100, .5) but $30 to ($100, .5), then four more choices might be presented between ($100, .05) and $28, $26, $24, $22. Another, maximally efficient approach is the *bisection method* in which each time a choice is made between two prospects (e.g., a risky and sure prospect), one of the outcomes is adjusted in smaller and smaller increments as preferences reverse. For instance, if a participant prefers $50 to ($100, .5) then he would be presented a choice between $25 and ($100, .5). If he prefers the sure amount this time, then he would be presented a choice between $37.50 and ($100, .5), and so forth. We note that unlike single-round elicitations, the multi-round and bisection approaches to eliciting certainty equivalents cannot easily be made incentive-compatible, because if a randomly selected choice is honored for real money, participants can game the system so that a greater number of choices offer higher sure amounts. Pragmatically, however, this method remains popular and there is no evidence that participants engage in such gaming.

Empirical tests indicate that the bisection method performs much better than direct elicitation of certainty equivalents (Bostic *et al*., 1990). Fischer and colleagues (1999) note that elicitation of certainty equivalents through a series of choices will suffer from some of the problems of direct elicitation when the goal of determining certainty equivalents is transparent. This can be obscured by eliciting choices in a staggered order so that each successive choice entails measurement of the certainty equivalent of a different prospect. The downside to this approach is that it is more time consuming than a more straightforward application of the bisection or sequential choice method that prices one prospect at a time.

## Modeling Choice Variability

The elicitation methods described thus far have all assumed a deterministic model of decision under risk. Naturally, one would not expect choices in practice to be 100% consistent. At different moments in time, a participant may reverse preferences between prospects. Such reversals may be due to decision errors (for example carelessness or lapses in concentration) and/or transitory variations in the participant's genuine underlying preferences (due, for example, to emotional, motivational, and cognitive states that influence risk preference). Reversals in preference are more likely to occur when the participant has difficulty distinguishing between prospects or has only weak preferences between them – if a decision maker is indifferent between prospects $g_1$ and $g_2$ then one would expect a 50% chance of reversing preferences on a subsequent choice between the prospects; the more strongly $g_1$ is preferred to $g_2$ the more often we expect it to be chosen. Such response variability is typically substantial in studies of risky choice. For instance, in a survey of eight studies of risky choice, Stott (2006, Table 1) found a median 23% rate of reversal in preferences when participants chose between the same pair of prospects on separate occasions within or across sessions.

There are two distinct approaches to modeling choice variability. The first is to assume that preferences are consistent with prospect theory but allow preferences consistent with that theory to vary from moment to moment. The *random preference* approach assumes that choices reflect a random draw from a probability distribution over preferences that are consistent with an underlying core theory (see Becker *et al*., 1963 for an articulation of such a model under expected utility and Loomes and Sugden, 1995, for a generalization). For instance, one could implement such a model using prospect theory value and weighting functions with variable parameters.

The second approach assumes a deterministic core theory but allows a specified error distribution to perturb the participant's response (see Becker *et al*., 1963 for an application to expected utility). Formally, let $f(g_1, g_2)$ be the relative frequency with which prospect $g_1$ is selected over prospect $g_2$ in a pairwise choice. Decisions are assumed to be stochastically independent from one another and symmetric so that $f(g_1, g_2) = 1 - f(g_2, g_1)$. Let $V(g_i)$ be the prospect theory value of prospect $g_i$. Most response variability models assume that $f(g_1, g_2)$ increases monotonically with $V(g_1) - V(g_2)$, the difference in prospect theory value of prospects 1 and 2.

The choice function $f(\cdot)$ can take several forms (see Stott, 2006, Table 4). First, it can manifest itself as a *constant error function* in which there is a fixed probability of expressing one's true preference. Thus, $f(g_1, g_2) = \varepsilon$ whenever $V(g_1) < V(g_2)$, $f(g_1, g_2) = 1/2$ whenever $V(g_1) = V(g_2)$, and $f(g_1, g_2) = 1 - \varepsilon$ whenever $V(g_1) > V(g_2)$, where $0 \le \varepsilon \le 1/2$. Second, choice frequency might depend on the difference in prospect theory value between prospects, either following a probit transformation (e.g., Hey and Orme, 1994) or a logit transformation (e.g., Carbone and Hey, 2000). Thus, for the probit transformation,

$$f(g_1, g_2) = \Phi[V(g_1) - V(g_2),\ 0,\ \sigma] \qquad \text{(A.27)}$$

where $\Phi[x, \mu, \sigma]$ is the cumulative normal distribution with mean $\mu$ and standard deviation $\sigma$ at point $x$. Third, the choice function might follow a Luce (1959) choice rule in which choice frequency depends on the ratio of prospect theory values of the prospects:

$$f(g_1, g_2) = \frac{V(g_1)^{\varepsilon}}{V(g_1)^{\varepsilon} + V(g_2)^{\varepsilon}}. \qquad \text{(A.28)}$$

In an empirical test of several stochastic models assuming expected utility compliant behavior, Loomes and Sugden (1998) found that the random preference model tended to under-predict observed violations of dominance, and the error model assuming a probit transformation tended to over-predict such violations. The constant error form performed poorly.

The most comprehensive test to date of various choice functions and prospect theory value and weighting functional forms was reported by Stott (2006), who tested various combinations, including most of those described in this chapter. In his test, the model with the greatest explanatory power (adjusted for degrees of freedom) relied on a power value function (V1), a Prelec (1998) one-parameter weighting function (W3B) and a logit function. However, for reasons mentioned, we recommend use of a two-parameter weighting function (W2).

### Reliability of Measured Parameters

Many applications of prospect theory parameter measurement rely on the assumption that measured parameters reflect stable individual differences. To date there have been surprisingly few empirical tests of this assumption, and the results have been mixed. Baucells and Villasís (2010) asked MBA students to complete a series of risky choices on two occasions three months apart. In particular, they observed the reflection effect (risk aversion for gains coupled with risk seeking for losses) among a majority of participants during both time periods, but considerable variation among individual participants' responses from one occasion to the next. However, when fitting the data to a stochastic choice model, an underlying reflection effect was documented among 72% of participants. In a related vein, Zeisberger and colleagues (2012) elicited prospect theory parameters from undergraduate students on two occasions one month apart. They found that while parameters were stable on the aggregate level, approximately one-sixth of participants exhibited significantly different parameters for the two administrations in the domain of gains and more than one-third of participants exhibited such parameter instability in the domain of losses. Using a similar design, Glöckner and Pachur (2012) elicited prospect theory parameter sets among undergraduate students during two sessions one week apart. Results indicated moderately high stability of individual differences in parameters across sessions, especially when using single-parameter weighting functions. Moreover, allowing for individual differences in CPT parameters measured at time 1 (time 2) yielded significantly better prediction of choices at time 2 (time 1) than did the median parameter estimate. While these results are encouraging, a study by Erner and colleagues (2013) carefully measured prospect theory parameters among business students, finding that they did a poor job predicting participants' preferences among prospects designed to mimic the profits of various financial products (e.g., binary call and put options). Taken together we conclude that measured prospect theory parameters reflect individual differences that are modestly stable, but more predictive of preferences among simple gambles than of more complex prospects.

## NEUROSCIENTIFIC DATA

There has been substantial progress in understanding the neural correlates of prospect theory in recent years (for an early review, see Trepel *et al.*, 2005). Below, the chapter first outlines some challenges to effective characterization of the relation between neural activity and theoretical quantities, and then reviews recent work that has characterized the brain systems involved in various components of prospect theory.

### Paradigmatic Challenges

Integrating theories from behavioral decision-making research with neuroscientific evidence has posed a number of challenges to researchers in both fields.

#### *Developing Clean Comparisons*

As developed in Chapter 6, a neuroimaging study is only as good as its task design. In particular, it is critical that tasks cleanly manipulate particular theoretical quantities or components. For example, a study designed to examine the nature of probability weighting must ensure that the manipulation of probability does not also affect value. Because it is often impossible to cleanly isolate quantities in this way using any specific task, another alterative is to vary multiple quantities simultaneously and then model these manipulations parametrically. This allows the response to each quantity to be separately estimated. For example, as noted in Chapter 9, Preuschoff and colleagues (2006) manipulated both expected reward and risk in a gambling task, and were able to demonstrate different regions showing parametric responses to each variable. A further challenge is that tasks that adequately isolate specific cognitive components may sacrifice their relevance to real-world decision-making, and thus provide decreased external validity to naturalistic decision making (Schonberg *et al*., 2011). Addressing this challenge will require the development of tasks that retain the excitement of real-world risk-taking experiences while still allowing clear cognitive decomposition.

### *Isolating Task Components*

One of the most difficult challenges of fMRI is the development of task paradigms and analytic approaches that allow isolation of specific task components. For example, in tasks where subjects make a decision and then receive an outcome, it is desirable to be able to separately estimate the evoked response to the decision and to the outcome. Because the fMRI signal provides a delayed and smeared representation of the underlying neuronal activity, the evoked response lags the mental event by several seconds. A number of earlier studies used an approach where specific timepoints following a particular component are assigned to that component; however, this approach is not a reliable way to isolate trial components, as it will provide at best a weighted average of nearby events (Zarahn, 2000). It is possible to model the individual components using the general linear model, but the regressors that model the different components are often highly correlated, resulting in inflated variance. One solution to this problem involves the use of random-length intervals between trial components; this serves to decorrelate the model regressors for each task component and allows more robust estimation of these responses (e.g., Aron *et al*., 2004), but it can also fundamentally change the nature of the task (Klein-Flügge *et al*., 2011).

### *Inferring Mental States from Neural Data*

It is very common in the neuroeconomics literature to infer the engagement of particular mental states from neuroimaging data. For example, Greene and colleagues (2001) found that moral decision making for "personal" moral dilemmas was associated with greater activity in a number of regions associated with emotion (for example the medial frontal gyrus) compared to "impersonal" moral dilemmas. On the basis of these results, they concluded that the difference between these tasks lies in the engagement of emotion when reasoning about the personal dilemmas. In a widely read and influential paper, Poldrack (2006) referred to this approach as *reverse inference*, and showed that its usefulness is limited by the selectivity of the activation in question. That is, if the specific regions in question only activate for the cognitive process of interest, then reverse inference may be relatively powerful; however, there is little evidence for strong selectivity in current neuroimaging studies, and this strategy should thus be used with caution. For example, ventral striatal activity is often taken to imply that the subject is experiencing reward, but activity in this region has also been found for aversive stimuli (Becerra *et al*., 2001) and novel non-rewarding stimuli (Berns *et al*., 1997), suggesting that this reverse inference may not be well founded. A formal analysis of reverse inference using the BrainMap database showed that ventral striatal activity did provide relatively good evidence in favor of the presence of reward (Ariely and Berns, 2010). An analysis of a ventral striatal location (MNI coordinates: $-8, 0, -12$) using the *Neurosynth.org* tool (Yarkoni *et al*., 2011) showed that the term "reward" had a fairly high likelihood (.8) of appearing in the paper given activation in that location (a reverse inference) but that there were a number of terms with stronger reverse inference probabilities, including "incentive," "odor," "trauma," and "losses." These results suggest continued caution in the use of reverse inference.

## Value Function

Before reviewing papers that purport to examine neurophysiological correlates of the prospect theory value function we pause to distinguish different varieties of utility, a discussion which formed the core of Chapters 1 and 9. Recall that traditionally, the utility construct in neoclassical economics refers to a hypothetical function that cannot be directly observed mapping states of wealth to numbers; a decision-maker whose choices adhere to the four axioms reviewed in Chapter 1 can be represented as maximizing expected utility. Thus, utility is a mathematical construct that may or may not reflect mental states of decision makers.

Although prospect theory also has an axiomatic foundation (Wakker and Tversky, 1993), the model is motivated by behavioral phenomena, such as the psychophysics of diminishing sensitivity, that are assumed to correspond to mental states of decision makers. However, it is important to distinguish different varieties of utility when using tools of neuroscience to interpret mental states of a decision maker, again, an issue that forms the core of Chapter 9's discussion of risk. In particular, "utility" in the context of making a decision may not be the same thing as "utility" in the context of experiencing or anticipating the receipt of an outcome. Economists have focused primarily on a measure of what Kahneman and colleagues (1997) call *decision utility*, which is the weight of potential outcomes in decisions. However, as these authors point out, the original concepts of utility from Bentham and others focused on the immediate experience of pleasure and pain, which they refer to as *experienced utility*. Others have highlighted the importance of the utility related to anticipating a positive or negative outcome (e.g., Loewenstein, 1987), referred to as *anticipation utility*. These are critical issues which form the subject of Chapter 18. Of particular interest is the fact that these different forms of utility can be dissociated; for example, individuals may make decisions that serve to decrease their experienced or anticipation utility. In order to be able to clearly interpret the results of neuroimaging studies, it is thus critical to distinguish between these different forms of utility. The distinction between different forms of utility in behavioral decision theory parallels the distinction between "wanting" and "liking" that has developed in the animal literature and reviewed in Chapter 18 (see also Berridge, 2007).

Because it is most directly relevant to the prospect theory value function, we focus here on decision utility. This is the value signal that is most directly involved in making choices, particularly when there is no immediate outcome of the decision, as in purchasing a stock or lottery ticket. This concept has received significant interest in recent years, and there is now convergent evidence for the role of ventromedial prefrontal cortex in representation of decision value, a conclusion developed in Chapters 8, 13, 21, and particularly 20. In one of the most important of the studies that led to this conclusion, Tom and colleagues (2007) imaged subjects during a gamble acceptability paradigm, in which subjects decided whether to accept or reject mixed gambles offering a 50% chance of gain and 50% chance of loss. The size of the gain and loss were varied parametrically across trials, with gains ranging from \$10 to \$40 (in \$2-increments) and losses from \$5 to \$20 (in \$1-increments). Subjects received an endowment in a separate session one week before scanning in order to encourage integration of the endowment into their assets and prevent the risk-seeking associated with house money effects (Thaler and Johnson, 1990). Subjects exhibited loss-averse decision behavior, with a median loss aversion parameter $\lambda = 1.93$ (range: 0.99 to 6.75). Parametric analyses examined activation in relation to gain and loss magnitude. A network of regions (including ventral and dorsal striatum, ventromedial and ventrolateral PFC, ACC, and dopaminergic midbrain regions) showed increasing activity as potential gain increased. Strikingly, no regions showed increasing activity as potential loss increased (even using weak thresholds in targeted regions including amygdala and insula). Instead, a number of regions showed decreasing activation as losses increased, and these regions overlapped with the regions whose activity increased for increasing gains. This finding of decreasing VMPFC activity for increasing losses has been replicated in several other studies (e.g., Cunningham *et al*., 2009; Plassmann *et al*., 2010); none of these studies have reported increased activity in regions such as insula or amygdala that are usually associated with negative outcomes.

The Tom and colleagues (2007) study further characterized the neural basis of loss aversion by first showing that a number of regions (including ventral striatum) showed what might be interpreted as *neural loss aversion*, meaning that the decrease in activity for losses was steeper than the increase in activity for gains. Using whole-brain maps of these neural loss aversion parameters, they found that behavioral loss aversion was highly correlated across individuals with neural loss aversion in a number of regions including ventral striatum and ventrolateral PFC. These data are strongly consistent with prospect theory's proposal of a value function with steeper slope for losses than gains. To our knowledge, no other published studies have directly attempted to replicate this analysis.

A number of studies have examined decision utility using a *willingness-to-pay* (WTP) paradigm in which subjects place bids for a number of ordinary food items in a Becker−DeGroot−Marschak (BDM) auction, which ensures that subjects' choices are an accurate reflection of their preferences. Plassmann and colleagues (2007) compared *free-bid* trials, in which subjects decided how much to bid on the item, with *forced-bid* trials in which subjects were told how much to bid. They found that activity in ventromedial and dorsolateral PFC was correlated with WTP in the free bid trials but not the forced bid trials, suggesting that these regions are particularly involved in coding for decision utility. Subsequent work using WTP paradigms has confirmed that the ventromedial PFC encodes decision utility across a broad range of goods (see for example Chib *et al*., 2009), suggesting that it serves as a final common pathway for value representation.

As noted in the first edition of this book, "Further work is necessary to better understand the amygdala's role in decision making," and indeed a number of studies have addressed this issue since the first edition, but the question still remains. Particularly provocative are the findings of De Martino and colleagues (2010), who found that two patients with amygdala damage due to Urbach–Wiethe syndrome did not exhibit loss aversion, suggesting in contrast to the imaging results that the amygdala is necessary for loss aversion. They suggest that this may have reflected the overall positive range of values for the decisions presented in the Tom and colleagues study; however, it is also possible that the differences reflect the fact that fMRI is sensitive to postsynaptic signals, and that the inputs to amygdala do not provide sufficient discrimination between different values. A recent study by Jenison and colleagues (2011) provides evidence consistent with this possibility. Amygdala neurons were directly recorded in three patients; of the 16 neurons whose spike rate correlated with WTP, nine showed a negative correlation, and seven showed a positive correlation. Thus, these neurons may cancel each other out in a parametric model, resulting in a lack of differential fMRI signals for gains and losses in spite of its importance. This work highlights the importance of lesion and neurophysiological studies alongside neuroimaging, given the clear limitations of each technique.

## Probability Weighting Distortions

A number of studies have attempted to identify neural correlates of distortions in probability weighting. Paulus and Frank (2006) used a certainty equivalent paradigm in which subjects chose between a gamble and a sure outcome on each trial; the gamble was altered on successive trials to estimate the certainty equivalent. Nonlinearity of the probability weighting function was estimated using the Prelec (1998) weighting function. Regression of activation for high versus low probability prospects showed that activity in the ACC was correlated with the nonlinearity parameter, such that subjects with more ACC activity for high versus low prospects were associated with less nonlinear weighting of probabilities.

Nonlinearities in probability weighting were also examined by Hsu and colleagues (2009). Subjects chose between pairs of simple gambles, which varied in magnitude and probability; on each trial, each gamble is first presented individually, then they are presented together and the subject chooses between them. Weighting function nonlinearity was estimated using the Prelec (1998) weighting function. In order to isolate regions exhibiting nonlinear responses with probability, separate regressors were created which modeled a linear response with $p$ and a deflection from that linear function which represents nonlinear effects. Significant correlations with both linear and nonlinear regressors were found in several regions, including the dorsal striatum. Further analysis of individual differences showed a significant correlation between behavioral nonlinearity and nonlinearity of striatal response across subjects.

Probability weighting distortion for aversive outcomes was examined by Berns and colleagues (2007). In a first phase, subjects passively viewed prospects which specified the magnitude and probability of an electric shock. In a second phase, subject chose between pairs of lotteries. A quantity was estimated (a *neurological probability response ratio* or NPRR) which indexed the response to a lottery with probability less than one to a lottery with a probability of one (normalized by respect to the response to probability $1/3$, which is the sampled point nearest to the likely intersection of the nonlinear weighting function and linear weighting function). For the passive phase, the NPRR was found to be significantly nonlinear for most regions examined, including regions in the dorsal striatum, prefrontal cortex, insula, and ACC. Activity from the passive phase was also used to predict choices during the choice phase; the fMRI signals provided significant predictive power, particularly for lotteries that were near the indifference point. Thus, there appears to be fairly widescale overweighting of low probability aversive events in a number of brain regions.

A recent study used positron emission tomography (PET, see Chapter 6 for details on this technique) to measure the relation between dopamine $D_1$ receptor binding and probability weighting distortions (Takahashi *et al.*, 2010; see Chapter 14 for more about these dopaminergic effects). They found that nonlinearity of the weighting function was associated with $D_1$ receptor density in the striatum, such that subjects with lower $D_1$ receptor densities as measured with PET showed a greater degree of nonlinearity. This result is potentially consistent with the foregoing studies; although the Takahashi study did not find an effect outside the striatum, the levels of $D_1$ receptor expression are much lower outside the striatum and thus the sensitivity to effects in those regions is much lower.

Although the results of these studies are preliminary and not completely consistent, they suggest that it should be possible to identify the neural correlates of probability weighting distortions and to resolve these issues in the near future. It will be important to determine which regions are causally involved in these distortions (as opposed to simply reflecting the distortions) by testing subjects with brain lesions or other neurological disorders for behavioral effects on probability representations. If nonlinearities are the product of a specific brain system, then it should be possible to find subjects whose choices are rendered linear with probability following specific lesions, similar to findings that ventromedial prefrontal cortex (vmPFC) lesions result in more advantageous behavior in risky choice (Shiv *et al*., 2005). It would also be useful to test the effects of pharmacological manipulations of the dopamine system, to confirm the role suggested by the Takahashi and colleagues (2010) results.

### Reference-Dependence and Framing Effects

The neural correlates of reference-dependence in decision making have been examined in several studies, but the upshot of these results are currently unclear. De Martino and colleagues (2006) manipulated framing in a decision task (discussed in detail in Chapter 24) in which subjects chose between a sure outcome and a gamble after receiving an initial endowment on each trial; gambles were not resolved during scanning. Framing was manipulated by offering subjects to choose between a sure loss and a gamble (for example: lose £30 versus gamble) or a sure win and a gamble (for example: keep £20 versus gamble). Subjects showed the standard behavioral pattern of risk-seeking in the loss frame and risk aversion in the gain frame, with substantial individual variability. Amygdala activity was associated with the dominant choices, with increased activity for sure choices in the gain frame and risky choices in the loss frame; the dorsal ACC showed an opposite pattern across conditions. Individual differences in behavioral framing-related bias were correlated with framing-related activation in orbitofrontal and medial prefrontal cortex; that is, subjects who showed less framing bias (and thus behaved more "rationally" in the technical sense) showed more activity for sure choices in the gain frame and risky choices in the loss frame compared to the other two conditions. Thus, whereas amygdala showed the framing-related pattern across all subjects on average, in the OFC this pattern was seen increasingly for subjects who showed less of a behavioral framing effect. This finding has been replicated by Roiser and colleagues (2009), who further showed that the effect was modulated by a polymorphism in the serotonin transporter gene. Although amygdala activation is often associated with negative outcomes, it has also been associated with positive outcomes (Weller *et al*., 2007), and the correlation of amygdala activity with choice in the De Martino and Roiser studies is consistent with coding of value in the amygdala.

The interpretation of the foregoing results is complicated, however, by a recent study of framing effects using the same task in patients with bilateral amygdala lesions. Talmi and colleagues (2010) found that these patients showed intact framing effects, contrary to the prediction of the neuroimaging studies. This result suggests that while the amygdala may be modulated by framing effects, it is likely not the region that is causing these effects.

Two other studies have examined reference dependence by comparing buying versus selling of similar objects. Knutson and colleagues (2008) found that the overall product preference was associated with activation in the ventral striatum, whereas vmPFC showed an interaction between buy/sell condition and price, as expected if it is coding for decision value. This study also found that individual differences in the size of the endowment effect were associated with activation in the insula, but only for activation to highly preferred items in the sell condition. While interesting, there is some concern that the analytic flexibility allowed by computing correlations for each subcondition may result in increased false positive rates (Simmons *et al*., 2011). In addition, this study did present the same items within both sell and buy conditions to each individual, and thus endowment effects were imputed rather than measured directly.

The neural basis of endowment effects was also examined by De Martino and colleagues (2009), who directly compared WTP and *willingness to accept* (WTA) for the same goods within subjects. They replicated the common finding of a correlation between WTP and VMPFC activation, whereas WTA on sell trials was associated with activation in a lateral orbitofrontal region. Both the bilateral striatum and insula showed a pattern indicative of the endowment effect (the difference between WTP/WTA and subjective expected value); the striatum showed this effect for both selling and buying, while the insula only on buy trials. In this study, individual differences in endowment effects (i.e., WTA − WTP) were correlated with striatal activity, both within subjects (across trials) and between subjects.

In summary, the neural basis of reference dependence and framing remains unclear, with different studies finding different regions (and sometimes the same region showing different effects). Further work is necessary to clarify the neural correlates and substrates of reference dependence. More detail on these issues can be found in Chapter 24.

## CONCLUSIONS AND FUTURE DIRECTIONS

The field of neuroeconomics is providing a rapidly increasing amount of data regarding the phenomena that lie at the heart of prospect theory, such as framing effects and loss aversion. But one might ask: what have these data told us about prospect theory? It is clear from the demonstrations of neural correlates of several of the fundamental behavioral phenomena underlying prospect theory (loss aversion, framing effects, and probability weighting distortions) that there is now mechanistic evidence for many of these violations of rationality which support pre-existing behavioral evidence. Our review of behavioral and neuroscience work on prospect theory and the neuroscience of behavioral decision making suggests a number of points of caution, however, for future studies of decision making in the brain:

1. It may be critical to distinguish between the different varieties of utility in designing and interpreting neuroscience studies, and this is particularly important when choosers are technically inconsistent – a point made in Chapter 8. Studies in which participants make a decision and then receive an immediate outcome may be unable to disentangle the complex combination of what Kahneman and colleagues (1997) have called decision, anticipated, and experienced utilities (see also Chapter 18) that are likely to be in play in such a task.
2. Under prospect theory, risk attitudes toward different kinds of prospects are interpreted in different ways. Risk aversion for mixed gambles is attributed to loss aversion; the fourfold pattern of risk attitudes for pure gain or loss gambles is attributed to diminishing sensitivity both to money (as reflected by curvature of the value function) and probability (as reflected by the inverse-S-shaped weighting function). It is easy to conflate these factors empirically; for instance, if one assumes a single-parameter weighting function that only allows variation in curvature but not elevation, then variations in observed risk attitudes across all probability levels may be misattributed to curvature of the value function.
3. Reverse inference (the inference of mental states from brain imaging data) should be used with extreme care. As a means for generating hypotheses it can be very useful, but its severe limitations should always be recognized (for more on this, see Poldrack, 2011).

## Challenges for the Future

In the first edition of this book, the prospect theory chapter argued that: "As neuroeconomics charges forward, we see a number of important challenges for our understanding of the neurobiology of prospect theory." Several years later, each of these challenges remains, though progress has been made on each.

First, there is a need to better understand the relations between different varieties of utility, both individually and in combination. This will require clever new approaches to experimental design in order to separate these entities. Second, it is critical that neuroimaging studies are integrated with studies of neuropsychological patients in order to determine not just which regions are correlated with particular theoretical phenomena, but also whether those regions are necessary for the presence of the phenomena. A nice example of this combined approach was seen in the study of ambiguity aversion by Hsu and colleagues (2005). It is likely that many of the regions whose activity is correlated with theoretical quantities (like curvature of the weighting function) may be effects rather than causes of the behavioral phenomena, a point highlighted by recent findings in which results from lesion studies diverged from imaging results (De Martino *et al.*, 2009; Talmi *et al.*, 2010). In addition, neurophysiological studies (where possible) can provide additional evidence regarding the nature of neural representations, as seen in the recent work by Jenison and colleagues (2011).

Another challenge comes in understanding the function of complex neural structures such as the ventral striatum and amygdala in decision making. Each of these regions is physiologically heterogeneous, but the resolution of current imaging techniques leads them to be treated as singular entities. In the amygdala the heterogeneous nuclei are large enough that they could potentially be differentiated using currently available neuroimaging methods (as in Etkin *et al.*, 2004), but little work has examined this distinction. The neurobiological heterogeneity of the ventral striatum is more difficult to address using current neuroimaging methods; there are both structural features that are not currently visible to human neuroimaging (accumbens core versus accumbens shell) as well as substantial cellular heterogeneity (striosomes versus matrix, direct versus indirect pathway) at an even finer grain. Finally, there is still substantial controversy over the degree to which imaging signals in the ventral striatum reflect dopamine release as opposed to excitatory inputs or interneuron activity. It is clear that imaging signals in the ventral striatum often exhibit activity that parallels the known patterns of dopamine neuron firing (in particular, prediction error signals), and dopamine has strong vascular as well as neuronal effects, so it is likely that it exerts powerful effects on imaging signals, but it is not currently known how to disentangle these effects from local neuronal effects. As an added complication, recent work has suggested that signals correlated with prediction error in the ventral striatum may reflect action-related signals rather than the pure prediction error signals that are coded by DA neurons (Klein-Flügge *et al.*, 2011). The use of voltammetry techniques

## BOX A.1

### FORMAL PRESENTATION OF CUMULATIVE PROSPECT THEORY

***(Adapted from Tversky and Kahneman, 1992)***

Let $S$ be the set whose elements are interpreted as states of the world, with subsets of $S$ called *events*. Thus, $S$ is the certain event and $\phi$ is the null event. A weighting function $W$ (on $S$), also called a *capacity*, is a mapping that assigns to each event in $S$ a number between 0 and 1 such that $W(\phi) = 0$, $W(S) = 1$ and $W(A) \geq W(B)$ if and only if $A \supseteq B$.

Let $X$ be a set of consequences, also called *outcomes*, that also includes a neutral outcome 0. An uncertain prospect $f$ is a function from $S$ into $X$ that assigns to each event $A_i$ a consequence $x_i$. Assume that the consequences are ordered by magnitude so that $x_i > x_j$ if and only if $i > j$. Cumulative prospect theory separates prospects into a positive part, $f^+$, that includes all $x_i > 0$, and a negative part, $f^-$, that includes all $x_i < 0$. CPT assumes a strictly increasing value function $v(x)$ satisfying $v(x_0) = v(0) = 0$.

CPT assigns to each prospect $f$ a number $V(f)$ such that $f \succcurlyeq g$ if and only if $V(f) \geq V(g)$. Consider prospect $f = (x_i, A_i)$, $-m \leq i \leq n$, in which positive (negative) subscripts refer to positive (negative) outcomes and decision weights $\pi^+(f^+) = (\pi_0^+, \ldots, \pi_n^+)$ and $\pi^-(f^-) = (\pi_{-m}^-, \ldots, \pi_0^-)$ for gains and losses, respectively. The value $V$ of the prospect is given by

$$V(f) = V(f^+) + V(f^-),$$

where

$$V(f^+) = \sum_{i=1}^{n} \pi_i^+ v(x_i), \text{ and } V(f^-) = \sum_{i=-m}^{0} \pi_i^- v(x_i),$$

where $\pi^+$ and $\pi^-$ are defined as follows:

$$\pi_n^+ = W^+(A_n),\ \pi_{-m}^- = W^-(A_{-m})$$
$$\pi_i^+ = W^+(A_i \cup \ldots \cup A_n) - W^+(A_{i+1} \cup \ldots \cup A_n), \quad \text{for } 0 \leq i \leq n-1,$$
$$\pi_i^- = W^-(A_{-m} \cup \ldots \cup A_i) - W^-(A_{-m} \cup \ldots \cup A_{i-1}), \quad \text{for } 1-m \leq i \leq 0.$$

to directly measure dopamine release, while challenging in humans (Kishida *et al.*, 2011), may represent the best approach to directly understand the role of dopamine in these functions.

Finally, one critical extension of present work will be to relate it to other work in the domain of cognitive control. The role of frontal and basal ganglia regions in the control of cognitive processes (including inhibition, selection, and interference resolution) is becoming increasingly well specified, but how these processes relate to decision has only recently begun to be explored. Recent work using *transcranial magnetic stimulation* (see Chapter 6) has shown that disruption of prefrontal cortical regions can directly modulate decision processes (e.g, Figner *et al.*, 2010), which suggests that this will continue to be a powerful approach to identify the role of prefrontal control systems in decision making.

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