CHAPTER

10

c00010 # Decisions Under Uncertainty: Psychological, Economic, and Neuroeconomic Explanations of Risk Preference

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OUTLINE

s0010 ## RISK PREFERENCE: THE HISTORICAL CONTEXT

p0010 Democratic and libertarian societies ask their citizens to make many decisions that involve uncertainty and risk, including important choices about pension investments, medical and long-term care insurance, or medical treatments. Risky decisions, from barely conscious ones when driving ("Should I overtake this car?") to carefully deliberated ones about capital investments ("Do I need to adjust my portfolio weights?") abound. As citizens have taken on more decision responsibility, unpredictability and uncertainty of decision outcomes has increased as the result of ever faster social, institutional, environmental and technological change.

It is no surprise, then, that the topic of decision-making under risk and uncertainty has fascinated observers of human behavior. From philosophers charged with providing tactical gambling advice to noblemen, to economists charged with predicting people's reactions to tax changes, risky choice and the selection criterion that people seek to optimize when making such decisions has been the object of theoretical and empirical investigation for centuries (Machina 1987; Glimcher, 2003). p0020

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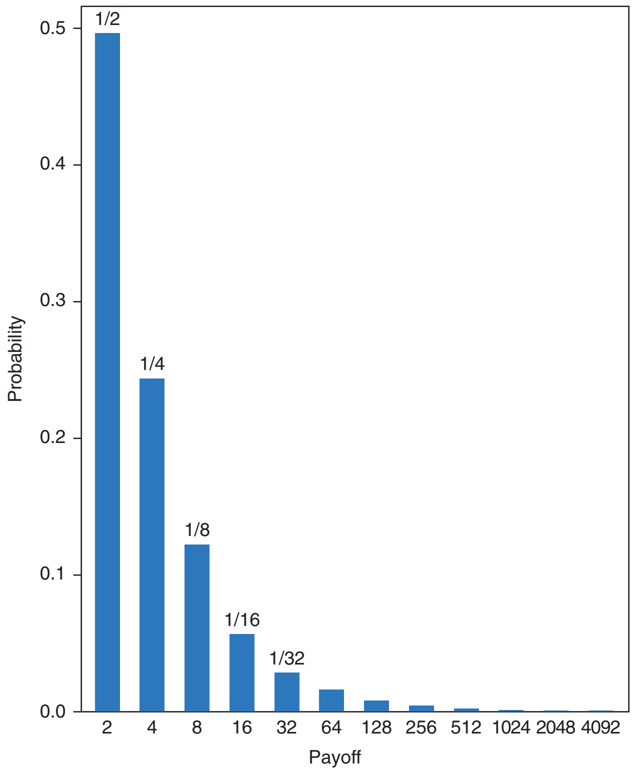

f0010 FIGURE 10.1 Payoff distribution for St Petersburg paradox game, where a fair coin is tossed until the first "head" is scored. The payoff depends on the trial at which the first "head" occurs, with \$2 if on the first trial, \$4 if on the second trial, and \$$2^n$ if on the nth trial.

s0020 Expected Value Theory

p0030 The maximization of expected (monetary) value (EV) of gamble X,

$$EV(X) = \sum_x p(x) \cdot x \tag{10.1}$$

first considered in the mid-seventeenth century, was rejected as a universally applicable decision criterion based on the so-called St Petersburg paradox, where people are willing to pay only a small price (typically between \$2 and \$4) for the privilege of playing a game with a highly skewed payoff distribution that has infinite expected value, as shown in Figure 10.1.

s0030 Expected Utility Theory

p0040 To resolve the St Petersburg paradox, Bernoulli (1954/1738) proposed that people maximize expected utility (EU) rather than expected value,

$$EU(X) = \sum_x p(x)u(x) \tag{10.2}$$

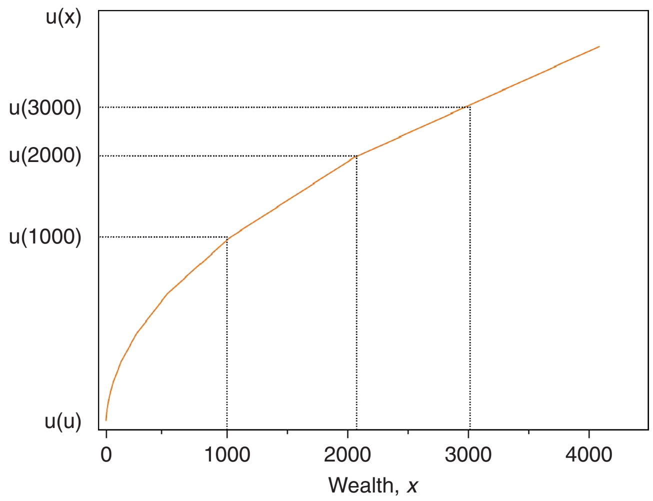

FIGURE 10.2 Concave utility function $u(x) = x^5$ which converts wealth, x, into its utility $u(x)$. An increase in wealth from \$0 to \$1000 is shown to result in a greater increase in utility than an increase in wealth from \$2000 to \$3000. f0020

postulating that money and wealth are diminishing in value, as shown in Figure 10.2. The function that maps actual wealth (x) on the x-axis into utility for wealth ($u(x)$) is no longer linear but "concave." An increase in wealth of \$1000 is worth a lot more at lower initial levels of wealth (from \$0 to \$1000) than at higher initial levels (from \$2000 to \$3000). In power functions, $u(x) = x^\theta$, for example, the exponent θ is a parameter that describes the function's degree of curvature ($\theta = .50$ in Figure 10.2) and serves as an index of an individual's degree of risk aversion. Such an individual difference parameter has face validity, as some individuals seem to resolve choices among options that differ in risk in very cautious ways ($\theta < 1$), while others seem willing to take on great risks in the hope of even greater returns ($\theta > 1$).

Von Neumann and Morgenstern (1947) provided an intuitively appealing axiomatic foundation for expected utility (EU) maximization, which made it a normatively attractive decision criterion not only for repeated decisions in the long run but also for unique risky decisions, and made EU maximization the dominant assumption in the economic analysis of choice under risk and uncertainty. See Chapter 3 of this volume for more detail on EU theory and its variants. p0050

Risk–return models s0040

In parallel to these developments in economics, Markowitz (1959) proposed a somewhat different solution to the St Petersburg paradox in finance, p0060

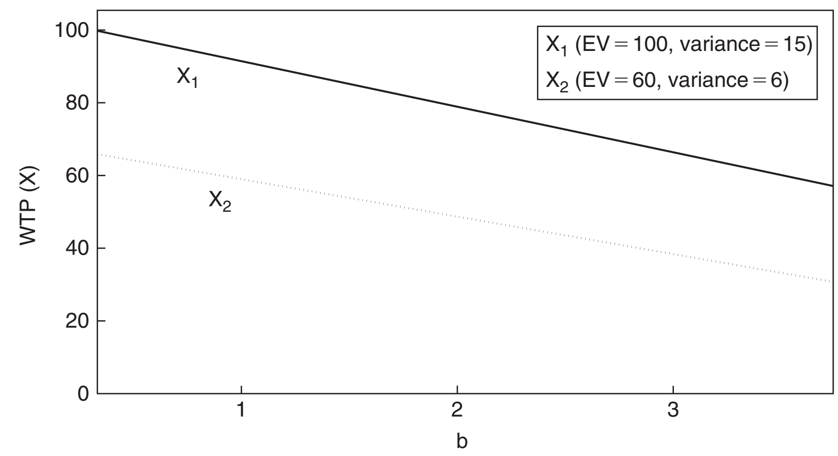

FIGURE 10.3 Willingess-to-pay (TWP) for risky investment options X (for X_1 (EV = 100, Variance = 15) and X_2 (EV = 60, Variance = 6)) as predicted by risk-return model in Equation 10.3, for different values of b. f0030

modeling people's willingness to pay (WTP) for risky option X as a tradeoff between the option's return $V(X)$ and its risk $R(X)$, with the assumption that people will try to minimize level of risk for a given level of return:

$$\mathrm{WTP}(X) = \mathrm{V}(X) - b\mathrm{R}(X) \qquad (10.3)$$

Traditional risk–return models in finance equate $V(X)$ with the EV of option X and $R(X)$ with its variance. Model parameter b describes the precise nature of the tradeoff between the maximization of return and minimization of risk, and serves as an individual difference index of risk aversion. Figure 10.3 shows how WTP varies for two gambles as a function of the tradeoff parameter b. This risk–return tradeoff model is widely used in finance, e.g., in the Capital Asset Pricing Model (CAPM; Sharpe, 1964; see Bodie and Merton, 1999, for more detail), and can be seen as a quadratic approximation to a power or exponential utility function (Levy and Markowitz, 1979). Other classes of utility functions also have risk–return interpretations, where returns, V(X), are typically modeled as the EV of the risky option, and different utility functions imply different functional forms for risk, $R(X)$ (Jia and Dyer, 1997).

p0070 Despite their prescriptive and normative strengths, both EU maximization and risk–return optimization have encountered problems as descriptive models for decisions under risk and uncertainty. Experimental evidence as well as choice patterns observed in the real world suggests that individuals often do not behave in a manner consistent with either of these classes of models (McFadden, 1999; Camerer, 2000). Human choice behavior deviates in systematic ways, as captured originally in two classical demonstrations referred to as the Allais (1953) and Ellsberg (1961) paradoxes, described below.

Limitations of Economic Risky Choice Models s0050

A central assumption of all economic risky choice models described above is that the utility of decision outcomes or the risk and return of choice options are determined entirely by the objective value of possible outcomes (and the final wealth they generate) in a "reference-independent" way, i.e., in a way that does not depend on what the outcome can be compared to. Thus the receipt of a \$100 is assumed to have the same effect on the decision of an individual, whether is it the top prize in the office basketball pool or the consolation prize in a lottery for \$1 m dollars. Decision-makers' evaluation of outcomes and choice options, however, appears to be influenced by a variety of relative comparisons (Kahneman, 2003). p0080

In fact it is now widely known that people often compare the outcome of their chosen option with the outcome they could have gotten, had they selected a different option (Landman, 1993). Such comparisons have an obvious learning function, particularly when the "counterfactual" outcome (i.e., the outcome that could have been obtained, but wasn't) would have been better. This unfavorable comparison between what was received and what could have been received with a different (counterfactual) action under the same state of the world is termed *regret*. When the realized outcome is better than the alternative, the feeling is called *rejoicing*. Consistent with the negativity effect found in many judgment domains (Weber, 1994), feelings of regret are typically stronger than feelings of rejoicing. Regret theory, independently proposed by Loomes and Sugden (1982) and Bell (1982), assumes that decision-makers anticipate these feelings of regret and rejoicing, and attempt to maximize EU as well as minimizing anticipated post-decisional net regret. Susceptibility to regret is a model parameter and an individual difference variable that dictates the p0090

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specifics of the tradeoff between the two choice criteria. Minimization of anticipated decision regret is a goal frequently observed, even if it results in lower material profitability (Markman *et al*., 1993). Extending these ideas, Braun and Muermann (2004) proposed a formulation of regret theory that can be applied to decisions that have more than two possible choice options. While post-decisional regret undoubtedly plays an important learning function, the importance to pre-decisional, anticipated regret is less clear. A recent set of choice simulations by Laciana *et al*. (2007) showed that the incorporation of anticipated regret into *EU* maximization did not result in risky choices that were significantly differently from those of *EU* maximization in a real-world risky decision domain, namely precision agriculture. In contrast, the actions prescribed by prospect theory value maximization, a theory described next, were considerably different from those prescribed by *EU* maximization.

s0060 Prospect Theory

p0100 Prospect theory (PT; Kahneman and Tversky, 1979; Tversky and Kahneman, 1992) introduced a different type of relative comparison into the evaluation of risky choice options, related to the $100 example above. As shown in Figure 10.4a, PT replaces the utility function u of *EU* theory with value function v, which is defined not over absolute outcomes (and resulting wealth levels) but in terms of relative gains or losses, i.e., as changes from a reference point, often the *status quo*. PT's value function maintains *EU*'s assumption that outcomes have decreasing effects as more is gained or lost (a property referred to by economists as "decreasing marginal sensitivity"). A person's degree of marginal sensitivity is measured by the parameter α in PT's power value function $v(x) = x^{\alpha}$. However, because outcomes are defined relative to a neutral reference point, the leveling off of increases in value as gains increase ("good things satiate") leads to a "concave" shape of the value function only in the domain of gains, as shown in Figure 10.4a. This concave shape is associated with risk-averse behavior, e.g., preferring the sure receipt of an amount much smaller than the expected value of a particular lottery over the opportunity to play the lottery. In contrast, the leveling off of increases in disutility as losses increase ("bad things lead to psychic numbing") leads to a "convex" shape of the value function in the domain of losses. This convex shape is associated with risk-seeking behavior, e.g., preferring a lottery of possible losses over the sure loss of an amount of money that is much smaller than the expected value of the lottery.

Another noteworthy characteristic of PT's value p0110 function is the asymmetry in the steepness of the function that evaluates losses and gains, with a much steeper function for losses ("losses loom larger"), also shown in Figure 10.4a. The ratio of the slope of the loss function over the slope of the gain function is referred to as *loss aversion*, and is another individual difference parameter, which is reflected by parameter λ. Empirical studies have consistently confirmed loss aversion as an important aspect of human choice behavior (Rabin, 1998; Camerer, 2005). It is also a likely explanation for real-world phenomena such as the endowment effect (Thaler, 1980), the *status quo* bias (Samuelson and Zeckhauser, 1988; Johnson and Goldstein, 2003), and the equity premium puzzle (Benartzi and Thaler, 1995), which describe behavior that deviates from the normative predictions of classical EU theory and risk–return models.

Just as PT suggests a subjective transformation p0120 of objective outcomes, it also suggests a psychological transformation of objective probabilities, p, into subjective decision weights, $\pi(p)$, which indicates the impact the event has on the decision. The original PT decision weight function, shown in Figure 10.4b, formalized empirical observations showing that small probability events receive more weight than they should, based on their likelihood of occurrence, while large probabilities receive too little weight. More recently, a more complex continuous function has been substituted (Tversky and Kahneman, 1992). See Chapter 11 of this volume for more details on PT.

PT also suggests that decision-makers will simplify p0130 complex choices by ignoring small differences or eliminating common components of a choice. These editing process are not well understood, or easily captured by a formal model. While PT is significantly more complex than *EU*, its psychological modifications explain many anomalous observations that have accrued over many years. Risk–return models have also undergone similar psychological modifications in recent years (Sarin and Weber, 1993), and are discussed in 'Modeling decision-making under uncertainty,' below.

DECISIONS UNDER UNCERTAINTY s0070

The models of risk preference introduced above, p0140 will be more formally revisited in the following section. In this section, we examine some distinctions between different types of uncertainty and different ways of reducing or resolving uncertainty. In the process of doing so, we discuss recent suggestions that dual-processing systems are involved in risky choice.

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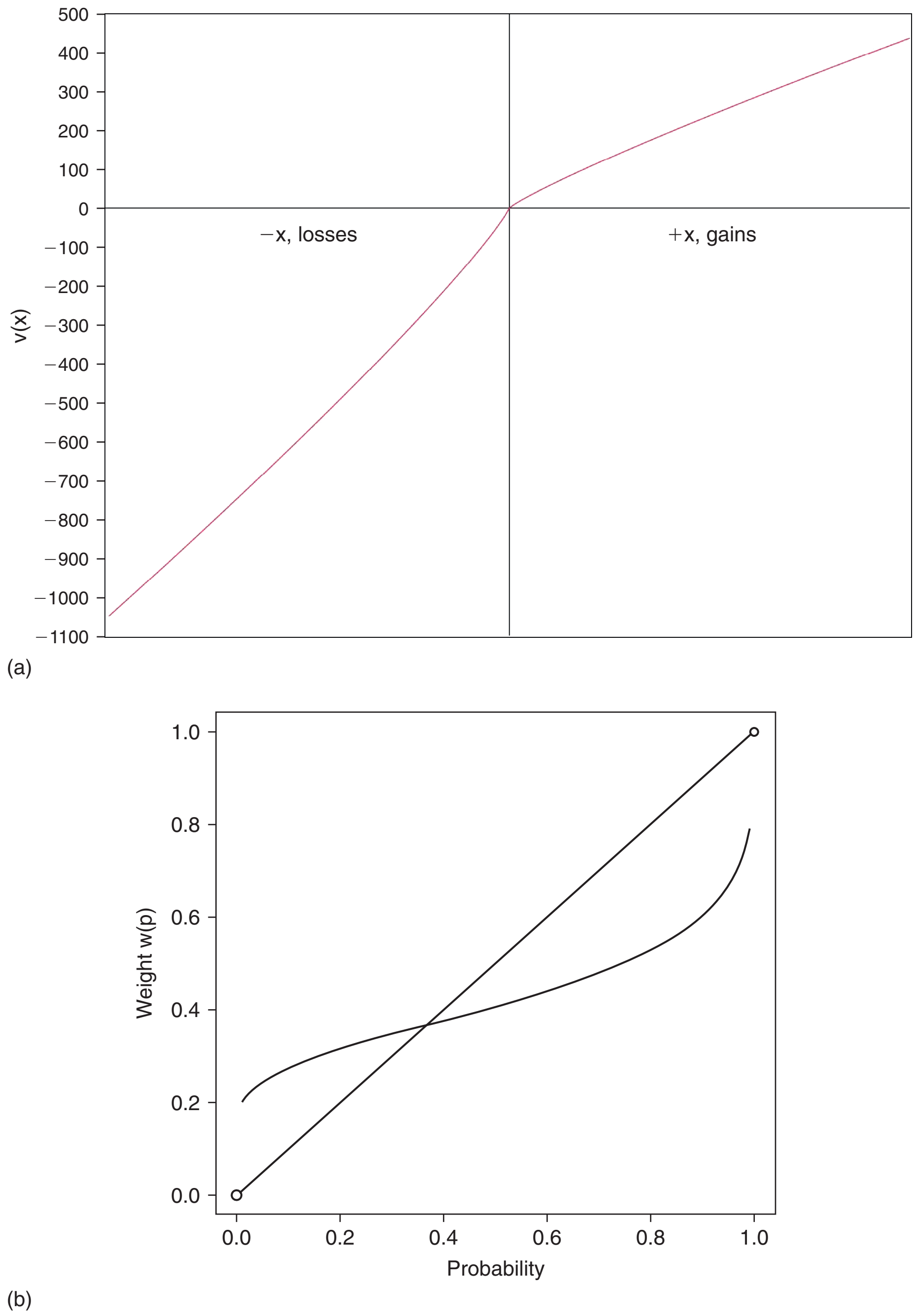

f0040 **FIGURE 10.4** Prospect theory's(1979) value function (a) $v(x)$ which is x^{88} for gains and $2.25 \bullet x^{88}$ for losses, and (b) decision weight function $\pi(p)$.

s0080 ## Uncertainty

s0090 ### *Types of Uncertainty*

p0150 Benjamin Franklin famously stated that the only things certain in life are death and taxes. If anything, the amount of uncertainty in our world has increased between the eighteenth and twenty-first centuries. A common distinction is made between *aleatory* uncertainty, i.e., objective and irreducible uncertainty about future occurrences that is due to inherent stochasticity in physical or biological systems, and *epistemic* uncertainty, which is subjective and reducible, because it results from a lack of knowledge about the quantities or processes identified with a system. The uncertainty associated with the outcome of the toss of a coin is an everyday example of aleatory uncertainty, whereas not knowing the chlorine level of your swimming pool is an example of epistemic uncertainty. While epistemic

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uncertainty is reducible in principle, many domains may have limits to the precision of predicting events far into the future, due to the complex or chaotic nature of the processes that are giving rise to them (Lempert *et al*., 2004). The social world provides uncertainties beyond those of the physical world, and game theory is a way of coping with the uncertainties that arise out of our limited ability to predict the behavior of others, as described in Chapters 5, 6, and 13 of this volume).

s0100 ### *Degrees of Uncertainty*

p0160 The economist Frank Knight was the first to make a conceptual distinction between decisions under *risk* and under *uncertainty* (1921: Ch. 7). *Risk* refers to situations where the decision-maker knows with certainty the mathematical probabilities of possible outcomes of choice alternatives. *Uncertainty* refers to situations where the likelihood of different outcomes cannot be expressed with any mathematical precision. Rational-economic analysis assumes that uncertain situations can be reduced to risky situations. In the absence of any information about probabilities, all possible values (in the extreme, between 0 and 1) should be assumed to be equally likely, with the midpoint of the range of possible likelihoods (e.g., .5) as the best estimate, a line of reasoning referred to as the "ignorance prior." Contrary to this assumption, Ellsberg (1961) showed that people clearly distinguish between risky and uncertain options and have a clear preference for the former – a behavior that Ellsberg called *ambiguity aversion*. (Some psychologists have argued that the word ambiguity ought to be reserved for situations that have a small number of possible interpretations – for example, the word "portfolio" referring to either a set of stocks held or to a set of artworks produced by a person. Situations that allow for a broad range of possible likelihoods of different events should be described as *vague*, and people's dislike of such situations as *vagueness aversion* (Budescu *et al*., 1988; Budescu and Wallsten, 1995), though this change in terminology does not appear to have been adopted.)

p0170 Knowledge about the probability distribution of possible outcomes of a choice can lie anywhere on a continuum, from complete ignorance (not even the possible outcomes are known) at one end, through various degrees of partial ignorance (where outcomes may be known, but their probabilities not precisely specified, denoted as uncertainty or ambiguity), to risk (where the full outcome distribution is precisely specified), to certainty (where only a single, deterministic outcome is known to result).

p0180 Ambiguity aversion has been observed in both laboratory experiments and in real-world health, environmental, and negotiation contexts (see Curley and Yates, 1989; Hogarth and Kunreuther, 1989). While ambiguity aversion is a very stable phenomenon, it is not universally observed (Camerer and Weber, 1992). If the ambiguous choice option is in a domain in which the decision-maker believes herself to have expertise, ambiguous options (e.g. sports bets) are often preferred to equivalent risky monetary lotteries (Fox and Tversky, 1995).

Ways of Resolving and Quantifying Uncertainty s0110

p0190 Epistemic uncertainty can be resolved in different ways. People and other organisms learn in a number of different ways, as described in Part 4 of this volume. Personal experience powerfully affects memory and subsequent behavior: a single painful touch of a hot stove can prevent similar mishaps for a lifetime. Observational learning is an evolutionary innovation available only to humans, primates, and a few other species (Zentall *et al*., 1988). Cultural learning, the ability to understand other's cautionary tales and anecdotes, extends the range of vicarious experience even further. Individuals who live in cooperative groups with the ability to communicate information in symbolic form can use the experience of others not just by direct observation, but also receive it in condensed form. The possible outcomes of investing in a particular company stock, for example, can be provided as a probability distribution of possible outcomes or as a time-series of past outcomes.

Multiple Processing Systems and the Resolution of Uncertainty s0120

p0200 Clinical (Epstein, 1994), social (Chaiken and Trope, 1999), as well as cognitive psychologists (Sloman, 1996; Kahneman, 2003) have recently proposed very similar dual-processing models of decision-making. Stanowich and West (1998) refer to the two hypothesized functional systems as "System 1" and System 2," others as rule-based or analytic versus experiential or associative systems. Which system is assumed to direct information processing in a given situation is often related to the way in which information about outcomes and their probabilities was acquired, over time from personal experience, or by external description (Erev and Barron, 2005).

p0210 Experiential processes correspond to the "concrete operations" described by Piaget (1962), while analytic processes are an example of his "formal operations," i.e., operations on ensembles of concrete experiences. Personal experience frequently contains strong

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feelings, making it memorable and therefore often dominant in processing (Loewenstein *et al*., 2001; Slovic *et al*., 2002). Strong feelings such as pleasure, pain, fear, and anger involve activation of a socio-emotional network of brain regions, in particular limbic and paralimbic structures, many of which are evolutionarily older than neocortical regions and found in all vertebrates (Cohen, 2005; Steinberg, 2007). By contrast, analytic processes that allow for planning, cognitive control, and self regulation involve prefrontal and parietal regions of the neocortex that have grown in size most in humans relative to other species (Cohen, 2005). The extent to which analytic processes occur in non-human animals is a subject of active investigation, though it seems clear that some processes, including those that underlie the syntactic structures of human language and the use of extended chains of logic, are uniquely human (Pinker, 1994).

p0220 Despite the current popularity of these dual-process explanations, not too strong a separation should be drawn between experiential and analytic processing (Keysers *et al*., 2008). Even simple reflexes can be influenced by neocortical processes, and analytic reasoning can lead to strong feelings. A given decision always involves and integrates both kinds of processes. The role of analytic processes in the understanding of uncertainty and in decisions involving such information has, however, often been overestimated, and the role of experiential processes has until recently not been sufficiently appreciated (Loewenstein *et al*., 2001).

p0230 Earlier in the chapter we discussed different ways in which human decision-makers can resolve epistemic uncertainty, from personal trial-and-error learning from the feedback provided by repeated sampling of available choice alternatives to the (external) provision of a numeric or graphic probability distribution of possible outcomes. The first of these ways has recently been labeled *decisions from experience*, and the second *decisions from description* (Hertwig *et al*., 2004; Weber *et al*., 2004). Research on decisions under these two ways of becoming knowledgeable about outcome distributions has historically been conducted in parallel by different research communities, with empirical research on human decision-making virtually exclusively employing decisions from description, and empirical research on animal learning and decision-making under uncertainty by necessity employing decisions from experience. Direct comparisons of choices under these two learning conditions in humans suggest that choices differ when small probability events are involved. (Differences in prediction between choices made by people under description (based on PT) vs under experience (based on reinforcement learning models like the Fractional Adjustment Model) start to occur when risky options contain probabilities less than .25, and tend to get larger the smaller the probabilities of some outcomes.) While rare events get more weight than they deserve by their probability of occurrence in decisions from description as modeled by PT's probability weighting function (Tversky and Kahneman, 1992), they tend to be underweighted in decisions from experience, unless they have recently occurred, in which case they are hugely overweighted (Weber, 2006). For more information on model differences and empirical results, see Weber *et al*. (2004).

MODELING DECISION-MAKING UNDER UNCERTAINTY s0130

In this section we revisit the two models introduced in their historical context at the beginning of this chapter, with the goal of showing how descriptive models of risky choice have built on them. Since *EU* theory and PT are described elsewhere (see Chapters 3 and 11 of this volume), we focus only on their general features and their commonalities to prescriptive and descriptive risk–return models of risky choice. p0240

Risk-taking and Risk Attitudes in EU and PT s0140

Not All Apparent Risk-taking May be Due to Risk Attitude s0150

Both the EU and the traditional risk–return approach to risky decision-making model differences in choice behavior with a single parameter, referred to as "risk attitude" or "risk tolerance." This parameter simply describes the curvature of the utility function or the slope of the risk–return tradeoff, and is identified empirically from a person's choices. For example, someone who is indifferent between $45 for sure and a 50/50 gamble between $0 and $100 is risk averse. The $5 difference between the EV of the gamble (i.e., $50) and the certainty equivalent of $45 is referred to as the risk premium. Greater risk aversion results in a larger risk premium. The label "risk attitude" suggests that such behavior is motivated by an attitude, typically a stable construct, i.e., a personality trait. p0250

Unfortunately for the interpretation of risk attitude as a personality trait, risk-taking is far from stable across situations for most individuals (Bromiley and Curley, 1992). The same person often shows different degrees of risk-taking in financial, career, health and safety, ethical, recreational, and social decisions p0260

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(MacCrimmon and Wehrung, 1986; Weber *et al.*, 2002; Hanoch *et al.*, 2006). This leaves two options. Either there is no stable individual difference in people's attitude towards risk, contrary to the intuition that people differ on this dimension, or we need to find a way to measure risk attitude in a way that shows stability across domains by factoring out other (more situationally determined) contributors to apparent risk-taking.

s0160 ***Constant and Relative Risk Aversion in EU***

p0270 EU explains the fact that people's certainty equivalents for lotteries typically are below the lotteries' EV by a concave function that turns objective amounts of money into their utility equivalent, with increasing amounts of money generating increased utility (positive slope, i.e., a positive first derivative), but less and less so (i.e., a negative second derivative). There is a large number of functions that have this general characteristic, not just the power function shown in Figure 10.2. Economists Kenneth Arrow and James Pratt thus tried to derive some measures of risk aversion independent of the utility function's functional form. They did so by linking risk aversion and the risk premium described above and, in particular, defined two indices that specified how a person's risk-taking would change as her wealth increases. There being more detail in Chapter 3 of this volume, we will only describe two types of effects here. The Arrow–Pratt (1964) measure of absolute risk aversion, defined as:

$$\mathrm{ARA}_u(x) = -u''(x)/u'(x) \tag{10.4}$$

where u' and u'' denote the first and second derivative of utility function u, specifies the absolute value of the risk premium associated with a given lottery. As shown in Figure 10.5 (left column), exponential utility functions have the property of constant absolute risk aversion (CARA), meaning that the decision-maker would pay the same risk premium to avoid the uncertainty of a given lottery (e.g., $5 for the 50/50 lottery between $100 or nothing) at all levels of wealth. Arrow (1965) more realistically assumed that most people show decreasing absolute risk aversion, i.e., would be more likely to play the gamble at higher levels of wealth, and thus pay a smaller risk premium to avoid it.

p0280 The other Arrow–Pratt measure, relative risk aversion, defined as:

$$\mathrm{RRA}_u(x) = -(x\,u''(x))/u'(x) \tag{10.5}$$

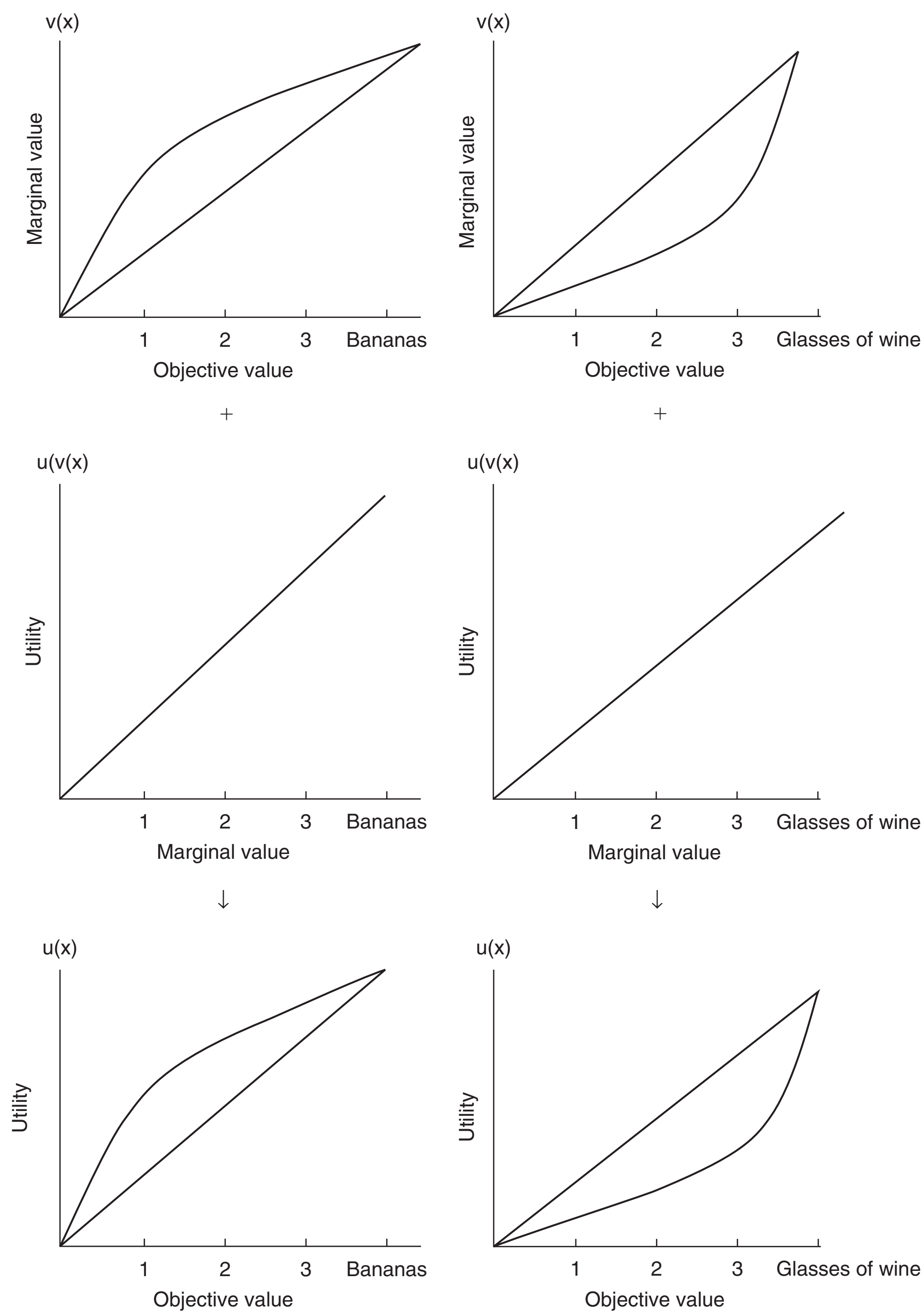
specifies the percentage value of wealth the *EU* maximizer is willing to put at risk. As shown in Figure 10.5 (right column), power utility functions have the property of constant relative risk aversion (CRRA), meaning that the decision-maker is willing to put the same percentage of wealth at risk (e.g., 40% in Figure 10.5) at all levels of wealth. Arrow (1965) assumed that instead, most people would show increasing relative risk aversion.

Accounting for Domain Differences in Risk-taking s0170

An early attempt to restore cross-situational consistency to the construct of risk attitude argued that utility functions derived from risky choices, $u(x)$, consist of two components, one measuring the (typically decreasing) marginal value ($v(x)$) of the outcome dimension (e.g., two bananas not being twice as rewarding as one banana), the other measuring the (typically averse) attitude towards risk, $u(v(x))$, which reflects a dislike of the fact that in a lottery one does not know for sure what one will get, resulting in the risk premium discussed above. In such cases, $u(v(x))$ is not as large as $v(x)$, and gets increasingly smaller the more $v(x)$ is at stake. If the index of the curvature of risky utility functions is the sum of these two contributions, then domain differences in curvature could be the result of the different marginal values for different outcomes dimension (e.g., the incremental value of an additional dollar vs the incremental value of an additional life saved), while the true attitude towards the risk or uncertainty with which these outcomes were obtained could be the same across domains. Figure 10.6 provides an example from a hypothetical person who has decreasing marginal value for additional bananas (shown in the top left panel) and slightly increasing marginal value for additional glasses of wine. As indicated in the middle panels, by the straight line that maps marginal value into utility, this person happens to have a completely neutral attitude towards risk, i.e., her anticipated enjoyment of bananas or glasses of wine is the same, regardless of whether these are acquired for certain or as part of a lottery. Because of the difference in marginal value, however, a utility function inferred from risky choices will show her to be risk averse for bananas (bottom left panel) but risk-seeking for glasses of wine (bottom right panel). Dyer and Sarin (1982) suggested that possible domain differences in riskless marginal value be factored out of an assessment of risk attitude, and thus replaced the Arrow–Pratt (1964) measure of ARA with what they referred to as *relative risk attitude*: p0290

$$-u''(v(x))/u'(v(x)) \tag{10.6}$$

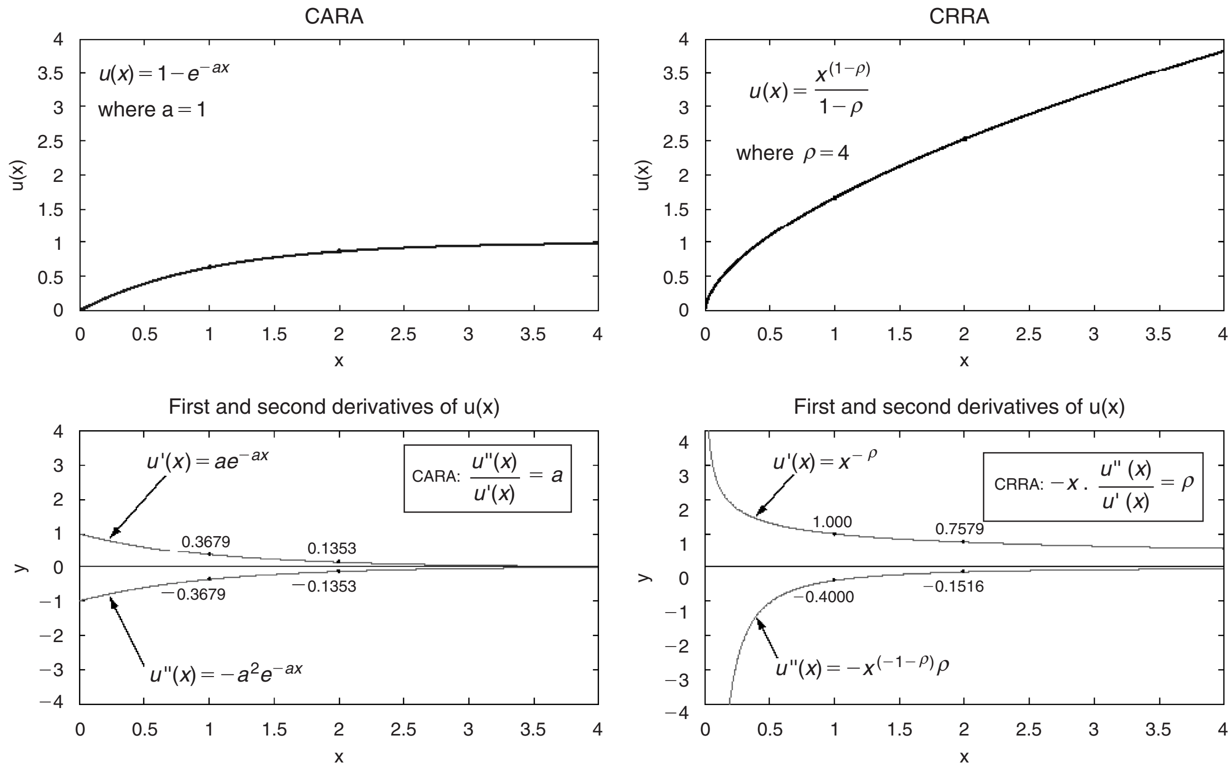
where $v(x)$ denotes the riskless marginal value function. When Keller (1985) compared people's



f0050 **FIGURE 10.5** Decomposition of utility function $u(x)$ (bottom row) into marginal value function $v(x)$ (top row) and attitude towards risk function $u(v(x))$ (middle row).

Arrow–Pratt measure of risk attitude (inferred from risky choices in various decision domains) to their relative risk attitudes (inferred from choices and marginal value functions in the same domains), she found that the two agreed in only a small number of cases, supporting the usefulness of unconfounding attitude towards uncertainty from non-linear marginal value. Unfortunately, relative risk attitudes did not show any more consistency across decision domains for any given respondent than the Arrow–Pratt ARA measure.

PT does not directly address the issue of inconsistency in risk-taking in different decision domains, but suggests other reasons we might see different risk-taking. Because a reference point divides outcomes into relative gains and relative losses, decreasing marginal utility produces a concave function and thus risk-averse choice for gains, but a convex function and thus risk-seeking choices for losses. In addition, the loss function has a steeper slope than the gain function (loss aversion), and probability weighting is p0300



f0060 **FIGURE 10.6** Constant absolute risk aversion (CARA, left column) and constant relative risk aversion (CRRA, right column). The top panel shows the described utility function, the bottom panel its first and second derivative.

non-linear. Thus PT, to the extent it is a descriptive theory of choice, suggests many reasons why risk-taking many seem unstable: First, the representation of the problem might change reference points, changing the apparent risk attitude. Second, to the extent that a person's decreasing marginal value or degree of loss aversion differs for outcomes in different domains, prospect theory could account for domain differences in risk-taking. Gaechter *et al*. (2007) provide evidence that loss aversion can differ for different attributes, in their case as a function of attribute importance and the decision-maker's expertise in the domain.

p0310 Behavioral extensions of risk–return models (Sarin and Weber, 1993) account for domain differences in risk-taking by questioning the equating of return with *EV* and of risk with outcome variance. While studies of financial decisions typically find that the *EV* of risky investment options presented in decisions from description is a good approximation of expected returns (Weber *et al*., 2005), survey data assessed in populations known to differ in actual risk-taking behavior suggest that risk-takers judge the expected benefits of risky choice options to be higher than do control groups (Hanoch *et al*., 2006). A large and growing literature has also examined perceptions of risk, both directly (by assessing people's judgments or rankings of the riskiness of risky options and modeling these, often on an axiomatic basis) and indirectly (trying to infer the best-fitting metric of riskiness from observed choices under the assumption of risk–return tradeoffs) (see Weber, 2001a, for further details. These studies are unanimous in their verdict that the variance or standard deviation of outcomes fails to account for perceived risk, for a variety of reasons. First, deviations above and below the mean contribute symmetrically to the mathematically defined variance, whereas perceptions of riskiness tend to be affected far more by downside variation (e.g., Luce and Weber, 1986). Second, variability in outcomes is perceived relative to average returns – a standard deviation of ±\$100 is huge for a risky option with a mean return of \$50, but amounts to rounding error for a risky option with a mean return of \$1 million. The coefficient of variation (CV), defined as the standard deviation (SD) that has been standardized by dividing by the *EV*:

$$\mathrm{CV}(X) = \mathrm{SD}(X)/\mathrm{EV}(X) \qquad (10.7)$$

provides a relative measure of risk, i.e., risk per unit of return. It is used in many applied domains, and provides a vastly superior fit to the risk-taking data of foraging animals and people who make decisions

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from experience (Weber *et al*., 2004). Weber *et al*. (2004) show that simple reinforcement learning models that describe choices in such learning environments predict behavior that is proportional to the CV and not the variance. Kacelnik and colleagues have explained animal risk-taking that is proportional to the CV, using a model called Scalar Utility Theory, which postulates that the cognitive representation of outcomes follows Weber's Law (1834) – namely, that the spread of the distribution of expected outcomes is proportional to its mean (see, for example, Marsh and Kacelnik, 2002).

p0320 Finally, affective (i.e., non-rational or non-consequential) responses to risky situations have been shown to play a large role in both the perception of the riskiness of risky choice options and in risky choice. The greater volatility in responses observed in decisions from experience relative to decisions from description, for example where behavior is influenced more by more recent experiences (an adaptive learning rule in non-stationary environments), can be seen as resulting from the salience of emotional reactions to recent outcomes. Familiarity with risky choice options or a risky choice domain lowers the perceptions of the choice options' riskiness (in evolutionary times, safer options provided longer periods of survival, with longer opportunities to acquire familiarity with choice options). The home bias effect in investing, i.e., the tendency to invest a larger than prudent amount of one's assets into stocks in one's home country or into stock of the company one works for, has been shown to be mediated by perceptions of lower risk of familiar investment opportunities (Weber, 2006).

s0180 *How to Measure Risk Attitude*

p0330 The behavioral research we reviewed strongly suggests that there is no single measure of "risk attitude" that can be inferred from observed levels of risk-taking. To find a person's true attitude towards risk (liking it for its excitement vs disliking it for the anxiety it induces) requires that we decompose observed risk-taking into the multiple factors (including risk attitude) that influence it. We would like to suggest that EU-based and other measures that simply re-describe the observed level of risk-taking (where greater risk-taking is typically operationalized as choosing options that have greater variance, while controlling for EV) use the term "risk-taking" instead.

p0340 One criterion for deciding how to assess individual differences in risky choice behavior is the purpose of the assessment, which usually falls into one of the following two categories: prediction or intervention. When measuring levels of risk-taking with the objective of predicting risk-taking in other situations, it is important to use a decision task that is as similar as possible to the situation for which behavior is being predicted. Given what we know about the domain-specificity and sign-dependence of risk-taking, assessment questions should come from the same domain and match the target situation in other respects. Weber *et al*. (2002) found that assessed risk-taking for monetary gambling decisions predicted real-world investment decisions far worse than assessed risk-taking for investment decisions, even though both were about monetary returns. Nosic and Weber (2007) confirmed that risk-taking for stock investments was not related to risk-taking for money lotteries, but was predicted by risk attitude, risk perception, and perceptions about return elicited in a stock-related context. It is thus not surprising that risk-taking indices like the level of relative risk aversion measure inferred by Holt and Laury (2001) from gambling choices, while widely used, have had only very mixed results in predicting risk-taking in other domains.

When intervention is the goal of efforts to assess individual differences in risk-taking (e.g., to make women less risk averse in their financial investment decisions), it becomes important to understand the causes of the apparent risk aversion or risk-seeking at a process level. One needs to understand whether apparently risk-averse decisions are driven by gender-specific differences in true attitude towards risk (e.g., women assessing risks and returns accurately, but disliking the risks more than men do), or whether other differences lie at the root of the gender differences in behavior (for example, differences in the subjective perception of risks or benefits, or differences in loss aversion). A more fine-grained assessment of determinants of risk-taking becomes important, because different causes of the behavior will dictate different interventions if seeking to effect change. p0350

Risk-taking and Risk Attitude in Psychological Risk–return Models s0190

Psychophysics, the study of the relationship between physical stimuli and their subjective perception, was the first topic of investigation of scientific psychology. The observed mappings between physical outcome dimensions (decibels) and subjective perception (loudness) were found to be not only non-linear, but also subject to context effects (see Weber, 2004). With the argument that similar non-linear and complex transformations might map objective outcome variation into perceived risk, and objective outcome *EV* into expected benefits, researchers from several disciplines (see Sarin and Weber, 1992) have recently p0360 generalized the normative finance risk–return model to allow for subjective perception of risks and returns which are, as before, traded off to determine willingness to pay (WTP) for risky option X:

$$\mathrm{WTP}(X) = V(X) - bR(X) \tag{10.8}$$

p0370 In these generalized psychophysical risk–return models, all three components, $V(X)$, $R(X)$, and tradeoff parameter b, are psychological variables, which can differ as the result of individual or situational characteristics. Behavioral evidence shows that the same objective outcome variation can be perceived in systematically different ways by different individuals and cultures (Brachinger and Weber, 1997; Weber, 2001a, 2001b). The characteristic that differentiates entrepreneurs from other managers, for example, contrary to managerial folklore, is *not* a more positive *attitude* towards risk, but instead an overly optimistic *perception* of the risks involved (Cooper *et al*., 1988). For outside observers who perceive risk more realistically, entrepreneurs will appear to take great risk; however, when differences in risk perception are factored out, entrepreneurs – just like other managers – demonstrate a preference for tasks that they see as only moderate in risk (Brockhaus, 1982).

p0380 When perceived risk and return replace the statistical moments of variance and EV in the prediction equation of risk-taking, the tradeoff coefficient b can be interpreted as an index of true attitude towards risk. Labeled *perceived risk attitude* (PRA) by Weber and Milliman (1997), it is a measure of the degree to which individuals find perceived risk attractive (or unattractive) and therefore will choose alternatives that carry greater (or less) risk, all other things being equal. Weber and Hsee (1998) obtained risk judgments as well as minimum buying prices for risky financial investment options from decision-makers in the USA, Germany, the People's Republic of China, and Poland. Both risk judgments and buying prices showed significant cross-national differences, with Americans perceiving the highest risks and Chinese paying the highest prices. However, after differences in risk perception were taken into consideration, the proportion of individuals who were perceived-risk averse or perceived-risk seeking were not significantly different in the four countries, with the majority being perceived-risk averse, and only a small percentage in each country being perceived-risk seeking.

p0390 Some psychologists have questioned the assumption of finance models that people will and should strive to minimize risk, arguing instead that people's ideal point for risk or uncertainty could differ, either as a personality difference (Lopes, 1987) or as a situational difference (Weber and Kirsner, 1997). Ideal-point models (Coombs, 1975) assume a person will perceive the riskiness of an alternative as the deviation between the alternative's level of uncertainty and the person's ideal point on the uncertainty continuum. Perceived risk of an alternative with a high objective level of uncertainty would be high for a person with a low ideal point, but low(er) for a person with a high ideal point. Individual differences in ideal points for risk and uncertainty have been measured by the construct of sensation-seeking (Zuckerman, 1979) which has a biological basis (Zuckerman *et al*., 1988) and varies with age and gender. Bromiley and Curley (1992) report evidence linking sensation-seeking to behavioral correlates that include greater risk-taking, especially in the health/safety and recreational domain. Weber *et al*. (2002) also report high positive correlations between sensation-seeking and its subscales in several content domains, with especially high correlations between the thrill-and-adventure-seeking subscale and recreational risk-taking, and the disinhibition subscale and ethical risk-taking. Consistent with the predictions of ideal-point models, the path by which differences in sensation-seeking seem to affect risk-taking appears to be differences in the perceptions of risk and of benefits, rather than differences in attitude towards perceived-risk. In other words, groups known for high levels of sensation-seeking (e.g., bungee jumpers or teenage boys) seem to take large risks because they perceive the risk to be smaller or the benefits to be larger than do other groups, and not because they cherish (perceived) risk to a greater extent (Hanoch *et al*., 2006).

Process-tracing Methods and Process Data s0200

Cognitive psychology has long tested models of risky choice using process analysis. The basic idea is to test models not just by their outputs, but also by their use of inputs and intermediate products. For example, EU models suggest that outcomes are weighted by their probability of occurrence. For process analysis, this suggests that decision-makers would look at each payoff and its probability *within* a choice alternative in close temporal order. In contrast, models that emphasize anticipated regret suggest that comparisons of the outcomes of different choice options for the same states of the world are relevant to choice, thus making a different prediction for information search from EU, namely a significant number of comparisons of pairs of outcomes *between* alternatives. p0400

A wide variety of process-analysis techniques exist, including asking people to talk aloud as they make p0410

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risky choices (see Ericsson and Simon (1993) for an review of the method, and Bettman and Park (1980) for an example). Information acquisition while making a choice has been examined by recording eye fixations on visually displayed information (Russo and Dosher, 1983) or, when using a computer to make a decision, by recording the mouse clicks that reveal information on the computer screen (Payne *et al*., 1991; Costa-Gomes *et al*., 2001; Gabaix *et al*., 2006; Johnson *et al*., 2008). In many ways, process analysis is a close relative of brain-imaging data, since the goal is to add other sources of data that inform models, and to provide additional constraints on theories.

p0420 When these techniques have been applied to risky choice, several facts emerge. First, complex displays (for example, lotteries with many outcomes or choices between many risky options) produce a different kind of processing than do simple choices between two binary lotteries. As posited by the editing phase of PT, when faced with complex displays or time pressure, decision-makers try to eliminate options and attend to only a subset of the available information. This suggests that imaging studies of risky choice that typically use very simple stimuli will speak to different processes than those used in more complex environments.

p0430 Second, even with simple choices, different ways of measuring preferences can invoke different choice processes. Consider the classic behavioral observations of inconsistent preferences across response modes, *preference reversals*. Here, people will choose one gamble over another but then, when asked to price the same two gambles, will give a lower price to the one they chose. These reversals (Lichtenstein and Slovic, 1971) provide a major source of evidence that EU is an incomplete model of decision-making under risk. Process data suggest that these reversals occur because people use different processes and put different weight on probabilities and payoffs when generating a price than when making a choice (Schkade and Johnson, 1989; Mellers *et al*., 1992). Observed preferences are not (just) an expression of inherent preferences; they also depend on the processes used to generate and express the preference.

p0440 Third, studies of choices between pairs of simple gambles tend to show some support for accounts that posit the weighting of outcomes by probabilities, consistent with EU and PT. While Brandstaetter *et al*. (2006) argue that a heuristic model, called the priority heuristic, that makes different and simpler comparisons than PT accounts for the same observed choices as PT, process-tracing studies show substantial inconsistencies with their heuristic model at a process level (Johnson *et al*., 2008).

Finally, there are marked individual differences in processes used to make risky choices. No single process seems to be used by all people, and there is significant evidence of shifts in strategies across different kinds of problems (Ford *et al*., 1989). In addition, there are strategy shifts when factors such as the time available to make a decision or the nature of the choice set changes (Ben Zur and Breznitz, 1981; Payne *et al*., 1988). p0450

Neuroimaging Studies and Data s0210

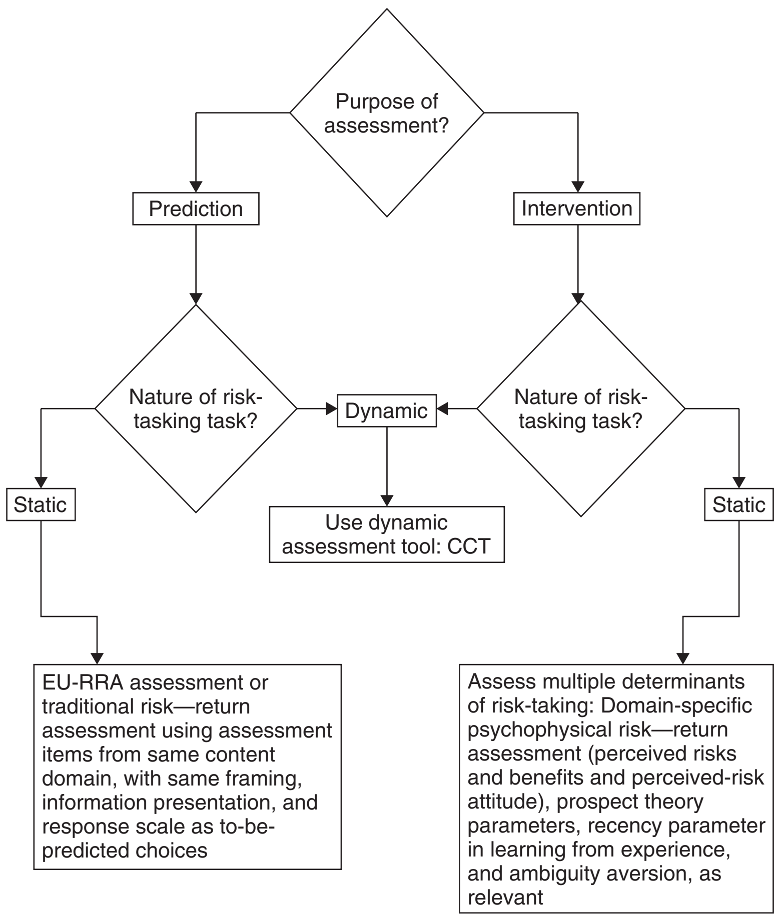
Neuroimaging techniques have added to our understanding of risky decision-making by providing evidence that hypothesized psychological processes and individual and situational differences in such processes have physical manifestations in brain processes. While this may seem obvious and unremarkable to some, it allows us to settle some long-standing arguments between psychologists and economists about the equivalence of different stimulus presentations, decision situations, or prior learning conditions. p0460

While the correct interpretation of both behavioral and neural results is not uncontroversial, comparisons of brain activation of people who choose between choice options that involve ambiguous outcomes vs choice options that involve the equivalent risky outcomes suggest that these two choice situations differ, and how (Hsu *et al*., 2005; Huettel *et al*., 2006). Neuroimaging studies suggest that there is strong path dependence in the brain's reaction to economic quantities like likelihood or risk/variance. While normative economic models do not distinguish between knowledge about the likelihood of different consequences that was acquired either by trial-and-error learning or by being given a statistical summary, as long as the accuracy of knowledge and source credibility are controlled for, then psychological models make different predictions for decisions from experience and decisions from description, and both process-tracing methodologies and neuroimaging data can be used to validate these accounts (Delgado *et al*., 2005). While it does not matter, to finance models of risk-taking, whether the expected value and variance of risky choice options is manipulated in a given choice set by varying the probabilities of different outcomes or their magnitudes (or both), neuroimaging studies that look at the effect of EV and variance on risk-taking tend to observe very different patterns of activation based on such differences in manipulation (Preuschoff *et al*., 2006 vs Grinband *et al*., 2007; also see Chapter 23 of this volume). Studies that have examined brain activation in response to gains vs losses, looking for the p0470 neural equivalent of loss aversion, also find different patterns of brain activation depending on whether each decision is resolved or not (Tom *et al*., 2007 vs Huettel *et al*., 2006), or whether people make decisions or just contemplate the options (Breiter *et al*., 2001).

s0220 SUMMARY AND IMPLICATIONS

p0480 Psychological and neuroscience studies of risk-taking have identified a wide range of factors, some exogenous and some endogenous, that influence risk-taking, as reviewed in this chapter. Multiple processes (some more effortful and analytic, others automatic, associative, and often emotion-based) are in play when a preference between different risky options is constructed. As decision-makers with limited attention and processing capacity, we need to be selective in what information we use, and have to find shortcuts to process it. Situational characteristics, like the way in which information about choice options is presented to us, or the nature of the task (e.g., choice vs a price judgment), influence risk-taking by focusing our attention on different subsets of information (e.g., the magnitude of outcomes for price judgments, their probabilities for choices) or by facilitating different relative comparisons in our search for the better option. Characteristics of the decision-maker (e.g., gender) often interact with characteristics of the situation (e.g., the domain of the decision) in determining risk-taking. This is either because different decision-makers use different processes to different degrees (e.g., decision-makers with greater cognitive capacity can make more use of effortful analytic processes – see Chapter 4 of this volume) or because the same processes result in different output (e.g., decision-makers familiar with a choice domain may experience positive emotions such as comfort or confidence when contemplating risky options in that domain, whereas decision-makers unfamiliar with the domain will experience negative emotions such as anxiety (Weber *et al*., 2005).

Figure 10.7 summarizes the implications of this chapter's review of the multiple determinants of risk preference for the frequently asked question: How can or should I assess the risk attitudes of a given group of decision-makers? As the flowchart indicates, the first diagnostic question that needs to be answered p0490



f0070 FIGURE 10.7 Decision tree for assessment of risk attitude.

in such situations is: Why are we assessing risk; what is the purpose of the desired assessment? If the purpose is simply to predict what decision-makers will do in (another) risky choice situation, the reasons for observed risk-taking need not be investigated. The main concern in such a predictive risk-taking assessment is to use a methodology that has high fidelity to the future risk-taking situation to which the predictive assessment will be applied. As discussed earlier in the chapter, risk-taking is often domain specific, which makes ostensibly "content-free" utility assessment tools like the Holt and Laury (2002) lotteries better predictors of risk-taking in monetary gambling choices than in risky agricultural production decisions. Weber *et al*. (2002) found that the gambling subscale of their Domain Specific Risk Taking (DOSPERT) scale was a significantly better predictor of self-reported gambling behavior than even of monetary investment decisions. This suggests that it is best to use domain-specific risk attitude assessment tools or to "translate" tools like the Holt and Laury lotteries into the domain context in which one is trying to predict.

p0500 Another important component of looking for a high-fidelity match between assessment tool and application is the nature of the risk-taking behavior that one is trying to predict. Much real-world risk-taking is incremental and dynamic, involving sequential risk-taking with feedback, from taking risks in traffic to risky substance (ab)use. Given what we have learned about the susceptibility of neural processing of risky decision situations to learning and feedback, it should come as no surprise that risk-taking in such dynamic contexts is typically not predicted by static assessment tasks, like one-shot lottery choices that are not resolved until the end of the assessment (Wallsten *et al*., 2005). If the risk-taking to be predicted is dynamic, dynamic task assessment tools like the Balloon Analogue Risk Task (BART; Lejuez *et al*., 2002) or the diagnostically more sophisticated Columbia Card Task (CCT; Figner *et al*., 2007) should be employed. These dynamic assessment tools come closer to repeated real-world investment or gambling decisions, in which previous outcomes often influence subsequent gambling or investment behavior, leading to such phenomena as gambling with house money (Thaler and Johnson, 1992), or escalation of commitment (Weber and Zuchel, 2005).

p0510 Even for static risk-taking applications, task and choice set differences often influence risk-taking behavior and thus should be controlled for by making the assessment tool similar to the target situation in those respects. Apparent risk-taking has been shown to vary when preferences between risky options are expressed in different ways, e.g., by choices vs bids vs buying prices vs selling prices (Lichtenstein and Slovic, 1971; Holt and Laury, 2002). Since gain vs loss framing of choice options and the way decision-makers have learned about outcome distributions affects risky choice, these variables should also be equated between the assessment and the to-be-predicted task.

Recommendations for assessment procedures get even more complicated for the right path in Figure 10.4, when the goal of the assessment is some intervention to change risk-taking in a target group of decision-makers. In these situations, we need to determine the cause(s) of taking more or less risk than is normatively desirable, because different causes call for different interventions. Researchers may have some hypothesis about the underlying cause (e.g., an inappropriate attitude towards risk), but this diagnosis needs to be established by assessments that (1) measure the construct "risk attitude" in ways that are not confounded with other possible causes, and (2) rule out competing diagnoses. Inferring an index of risk aversion based on some assumed functional form for utility from a set of choices simply will not suffice, as discussed previously. Rather than assessing a single parameter (absolute or relative risk aversion) from such choices, at the very least the three individual difference parameters of PT should be assessed, to determine whether loss aversion or distortions in probability weighting contribute to the observed behavior or whether it is only due a decreasing marginal utility or value. In addition, decision-makers' perceptions of a choice option's risks and returns can be assessed and evaluated for accuracy. Regressing observed preference (e.g., willingness to pay) for risky options on perceptions of risks and returns allows for an assessment of true risk attitude, i.e., positive or negative reaction to risk as it is perceived. p0520

While the behavior of people in situations of risk and uncertainty is complex and multiply determined, the broader set of tools provided by a psychological and neuroeconomic understanding of risk preference allows for a far more nuanced assessment and understanding of both general behavior patterns and individual or group differences in behavior. To the extent that psychology and neuroscience help explain the departures from the normative models described by economics, better interventions can be developed. Given the importance of accurate predictions of risk preference and of effective interventions to modify socially undesirable levels of risk-taking, we expect that the success of neuroeconomic methods will significantly contribute to greater acceptance of behavioral models by traditional economics. p0530 s0230 ## Acknowledgments

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