Chapter to appear in G. Keren & G. Wu (Eds.). *Handbook of Judgment and Decision Making*.



# Decision Under Risk:

# From the Field to the Lab and Back

Craig R. Fox [1,2]

Carsten Erner [1]

Daniel J. Walters [1]

1 UCLA Anderson School of Management

2 UCLA Department of Psychology

*Corresponding Author*:
Craig R. Fox
UCLA Anderson School of Management
110 Westwood Plaza #D511
Los Angeles, CA 90095-1481
craig.fox@anderson.ucla.edu

*Acknowledgments*:
We thank Vitalie Spinu, David Tannenbaum, the Editors, and two anonymous reviewers for valuable comments on an earlier draft this this chapter.

## 1. Introduction: From the Field to the Lab

Few topics attract as much attention across the social and behavioral sciences as risk. Enter "risk" as a search term in *Google* or in the books section at *Amazon*, and you will turn up more results than searches for terms such as "judgment," "decision," or even "happiness." Despite all of this interest, most lay people, professionals, and clinical researchers understand risk very differently than do decision theorists. For instance, the *Oxford English Dictionary* defines risk as "exposure to the possibility of loss, injury, or other adverse or unwelcome circumstance; a chance or situation involving such a possibility." That accords with the clinical definition of risk which includes behaviors that can result in loss or harm to oneself or others such as skydiving, recreational drug use, and unprotected sex (e.g., Furby & Beyth-Marom, 1992; Steinberg, 2008), and it likewise accords with the view of managers who see risk as exposure to possible negative outcomes (March & Shapira, 1987). Psychometric studies of risk intuitions similarly implicate exposure to potential dangers, revealing a *dread* component that is characterized by lack of control or potential catastrophic consequences, and an *unknown* component that is characterized by unobservable, unknown, or delayed consequences (Slovic, 1987).

An important problem with the lay conception of riskiness is that its major elements—loss, lack of control, unknown consequences—do not lend themselves to a coherent operationalization of the construct. Surely an option can be risky without the possibility of a loss—for instance, {gain $100 if a fair coin lands heads or else gain nothing} appears more risky than {gain $50 for sure}. Surely a decision maker's apparent control over the process generating outcomes does not always affect their riskiness—the risk inherent to the $100 coin flip should not be affected by whether or not the decision maker is the one doing the flipping (even though most people would rather bet on their own flip; see Langer, 1975). Surely an option can be risky even when there is nothing unobservable, unknown, or delayed—the $100 bet on a coin flip is risky even though the process is observable, the potential outcomes and their respective probabilities are perfectly known, and the resolution is immediate.

Decision theorists avoid such interpretive inconsistencies by building their models as functions of objective properties of probability distributions over possible outcomes. While no single definition of comparative riskiness holds across all models, it is generally seen as increasing with variation in the outcome distribution, holding expected value constant. For instance, {a 50% chance to gain $100 or else gain nothing} is generally considered to be more “risky” than {a 50% chance to gain $60 or else gain $40} because the variance of the first prospect is greater than the variance of the second prospect, while both yield the same expected value (that is, the former distribution is a “mean-preserving spread” of the latter distribution; see Rothschild & Stiglitz, 1970). Note that this particular operationalization of comparative riskiness does not take into account the higher moments of the distribution, such as skewness, and different measures may order prospects in terms of their riskiness in different ways. Furthermore, relative riskiness does not necessarily translate into a preference relation over any two gambles, as the mapping of riskiness to preference depends on the particular decision model. Nevertheless, most models agree that any chance prospect is more “risky” than a sure outcome equal to its expected value. Thus, a person is considered *risk averse* if she prefers a sure amount to a chance prospect of equal or higher expected value; she is *risk seeking* if she prefers a chance prospect to a sure amount that is equal to or less than its expected value, and she is *risk neutral* if she is indifferent between a chance prospect and a sure amount equal to its expected value.

Decision theorists since Knight (1921) have distinguished *decision under risk,* in which the probability distribution over possible outcomes is known precisely by the decision maker, from *decision under uncertainty*, in which it is not known but might be assessed with some degree of vagueness or imprecision. Thus, a choice whether or not to wager $100 that a fair coin will land "heads" on the next flip is generally construed as a decision under risk, whereas a choice whether or not to wager $100 that the home team will prevail in its next match is generally construed as a decision under uncertainty. In this chapter, most of our focus will be on studies of decision making under risk, though we will briefly examine how insights from studies of risky choice can be extended more generally to uncertainty. Other chapters in this volume will discuss at greater length decision making when the probability distribution is unknown (Chapter 3) or learned through a sampling process (Chapter 10).

Before we can examine the antecedents of risk taking in the field, it is important to note that many naturalistic observations of risk taking that could be construed as choices of higher variability options are driven by factors that have little to do with risk preferences *per se*. For instance, a person choosing to have unprotected sex may be focusing on immediate pleasure and steeply discounting possible future negative consequences; an adolescent who uses a recreational drug may be acquiescing to peer pressure that overwhelms her covert trepidation that would otherwise hold her back from such activity; an intrepid rock climber may underestimate the probability or severity of potential accidents so that she does not see the activity as particularly risky. All of these factors (present bias, response to social pressure, different perceptions of probabilities and/or outcomes) may contribute to behaviors that are construed as risk taking, even though they are not driven by an appetite for risk *per se.* To best understand what drives *attitudes toward risk*, we must strip away all such complications and focus on decisions involving simple, well-defined chance gambles in which there is no question about the decision maker's construal of the probabilities and possible consequences of her choices. After we understand factors that underlie distilled risk preferences, we can add back such additional drivers to enhance our ability to predict naturalistic risk taking behaviors.

In this chapter we provide an overview to decision making behavior under risk. We do so by first retreating from the field to the laboratory, setting aside for the moment the richness of naturalistic environments to get at the essence of risk and risk taking. In the section that follows we will take stock of the major insights derived from laboratory experiments of decision under risk, using choices between simple chance gambles. In so doing, we devote special attention to the dominant behavioral model, *prospect theory*, take stock of major challenges to this theory, and examine some alternative models that have been proposed. We then return to the question of how we can build on insights from laboratory research to better predict risky behaviors in naturalistic environments. Toward that end, we introduce a conceptual framework characterizing three steps for constructing models of risk taking in naturalistic environments (select a baseline model, determine model variables, determine model parameters) at different levels of analysis (typical behavior, individual differences, state differences).

We hope that this chapter can serve as a useful resource for students and researchers new to the field, experts in behavioral decision research, and practitioners. Students and researchers new to the field should treat this chapter as a broad overview to behavioral research on decision making under risk that will point them to additional sources for deeper study on topics of interest. Researchers with prior expertise in the study of decision making might find this chapter most useful as a review of alternative behavioral models of risky choice (Section 3) as well as a framework for applying models of decision under risk in the field (Section 4). We suggest that practitioners and others desiring a quick “crash course” will be best served by focusing on our discussion of the dominant paradigms (Sections 2.1-2.2) and skipping our discussion of new challenges and alternative models (Sections 2.3, and 3 respectively).

Before proceeding we note that there are a number of excellent prior reviews of decision under risk. Some provide broad historical overviews to the decision theoretic literature (e.g., Camerer, 1995; Mellers, Schwartz, & Cooke, 1998; Starmer, 2000; Wu, Zhang, & Gonzalez, 2004) while others focus on specific topics within decision under risk. Multiple reviews exist on the transition from expected value to prospect theory (e.g., Chiu & Wu, 2010; Machina, 1987b) and axiomatic descriptions of expected utility theory (e.g., Barberà, Hammond, & Seidl, 2004; Schoemaker, 1982). Recent reviews have been written on prospect theory and parameter elicitation techniques (e.g., Fox & Poldrack, 2014; Wakker, 2010), on limitations and descriptive violations of prospect theory (e.g., Birnbaum, 2008a), and on prospect theory in field studies (e.g., Barberis, 2013). Other reviews examine the distinction between decision under risk versus uncertainty (e.g., Fox & See, 2003; Machina, 1987a). There are also discussions of individual differences in risk preferences (e.g., Fox & Tannenbaum, 2011) and the interaction of individual differences and situational characteristics on risk taking (Figner & Weber, 2011). Finally, some reviews have examined the role of affect in decisions under risk (e.g., Loewenstein, Weber, & Hsee, 2001; Rottenstreich & Shu, 2004; Trepel, Fox, & Poldrack, 2005) or have taken stock of neuroscientific developments (Fox & Poldrack, 2014; Schonberg, Fox, & Poldrack, 2011).

# 2. Modeling Risky Choice

## 2.1 From Expected Value Maximization to Prospect Theory

### *Expected Value Maximization*

The most popular models of decision under risk are integration models, representing preferences as an average of some function of outcomes weighted by some function of their respective probabilities. The first rudimentary integration model can be traced to a correspondence in 1654 between Fermat and Pascal that laid the mathematical foundation for probability theory. *Expected value maximization* posits that people ought to choose options that have the highest expected value. Consider a prospect $\{x,p\}$ that offers \$$x$ with probability $p$. The expected value (EV) of this prospect is simply the product of the probability and outcome:

$$\text{EV} = px.$$

For example, the expected value of a prospect that offers {a 50% chance to gain \$100 or else gain nothing} is $.5 \times \$100 + .5 \times \$0 = \$50$. Thus, early probability theorists assumed that the gamble ought to be chosen over say, {gain \$20 for sure} because the expected value of the chance prospect exceeds the sure amount. While this decision rule is elegant in its simplicity and offers a recipe for maximizing long-run aggregate outcomes over multiple identical choices (assuming that one is not bankrupted in the process), it is inadequate in explaining observed behavior because it imposes risk neutral preferences on decision makers. Thus, it cannot explain why people would buy lottery tickets or insurance, or why a person might reasonably prefer to be cautious when making a unique decision with large consequences, such as having an operation or buying a house. For instance, an EV maximizer would rather have {a 90% chance to gain \$1,000,000 or else gain nothing} than {gain \$899,000 for sure}. We suspect that most readers of this chapter would choose the sure amount in this case.

A crisper example, known as the *St. Petersburg Paradox*, entails a gamble in which a fair coin is tossed repeatedly until it lands heads for the first time, and the prize amount is determined by the toss number, $n$, on which the first heads occurs. The prize amount is given by $\$2^n$. It is easy to see that the expected value of this gamble, given by $1/2 \times (\$2) + 1/4 \times (\$4) + 1/8 \times (\$8)$ ..., is infinite. Nevertheless, very few people would choose this gamble over a large finite certain amount such as one million dollars.

***Expected Utility Theory***

In response to such challenges to the descriptive validity of expected value maximization, Swiss mathematician Daniel Bernoulli (1738) asserted that decision makers choose options that maximize expected "moral value" or *utility* of outcomes, $u(x)$. Thus, the expected utility (EU) of an option that offers outcome $\$x$ with probability $p$ is given by:

$$\mathrm{EU} = p\,u(x).$$

The subjective value of money is assumed to decrease with each additional dollar added to a decision maker's cumulative wealth (see Figure 1). For instance, gaining \$100 has greater impact on the subjective experience of a person when poorer (wealth level $W_1$) than this person when wealthier (wealth level $W_2$). Thus, the difference between $u(W_1)$ and $u(W_1 + \$100)$ is greater than the difference between $u(W_2)$ and $u(W_2 + \$100)$, i.e., $\Delta u_1 > \Delta u_2$ in Figure 1. Such a pattern of continuously diminishing marginal utility yields a concave shaped utility function and can also explain risk aversion, as can be seen in Figure 2. For instance, if adding \$50 to one's current state of wealth (wealth level $W_0$) brings more than half the utility of adding \$100, then a person should prefer {gain \$50 for sure} to {a 50% chance to gain \$100 or else gain nothing}, because $u(W_0 + \$50) > .5\,u(W_0 + \$100) + .5\,u(W_0)$.

[Insert Figure 1 about here.]

[Insert Figure 2 about here.]

The impact of expected utility theory in the social sciences grew precipitously after von Neumann and Morgenstern (1947) provided an axiomatic foundation for EU as an appendix to their landmark *Theory of Games and Economic Behavior.* That is, they articulated a set of qualitative principles that are necessary and sufficient for treating decision makers as expected utility maximizers. Thus, if a person's decisions consistently satisfy a small set of qualitative conditions then one can model his choices using the mathematics of EU while remaining agnostic concerning the cognitive process underlying his behavior. The most important of these axioms are *completeness, transitivity,* and *independence*. Completeness states that the decision maker has defined preferences over all possible pairs of options. Transitivity stipulates that if a decision maker prefers option A to option B and option B to option C then she must also prefer option A to option C. For example, if John prefers an Audi to a Buick and a Buick to a Chevrolet then he should also prefer an Audi to a Chevrolet. Transitivity and completeness are necessary to map options onto a well-ordered utility scale. The independence axiom states that a person should prefer option $f$ to option $g$ if and only if he prefers a probabilistic mixture of $f$ and some third option $h$ to a similar probabilistic mixture of $g$ and $h$. For example, John should prefer an Audi to a Buick if and only if he prefers {a 50% chance to get an Audi and otherwise get a Chevrolet} to {a 50% chance to get a Buick and otherwise get a Chevrolet}. Independence is essential for weighting utilities of outcomes by their respective probabilities in an additively separable manner.

The axiomatization of EU is a profound intellectual achievement, and the axioms seem on their surface to be compelling standards of behavior. However, almost since its inception the descriptive validity of EU has faced a number of challenges. Here, we highlight three challenges:

The Allais paradox, the fourfold pattern of risk attitudes, and the observation that typical patterns of risk aversion cannot be explained by the curvature of the utility function.

***Challenge 1: The Allais paradox***

Perhaps the most striking early challenge to expected utility theory is known as the *Allais paradox* (Allais, 1953), one version of which is as follows:

*Decision 1*: Choose between:

*f*: {a 100% chance to gain $300}

*g*: {an 80% chance to gain $400 or else gain nothing}

*Decision 2*: Choose between:

*f'* {a 25% chance to gain $300 or else gain nothing}

*g'* {a 20% chance to gain $400 or else gain nothing}

Most people prefer *f* over *g* but they prefer *g'* over *f'*, a striking violation of the independence axiom (note that *f'* and *g'* are mixtures of a 25% chance of receiving *f* and *g* respectively, with a 75% chance of receiving nothing). This violation becomes more apparent when we re-write the prospects in terms of their expected utilities:

$\mathrm{EU}(f) = u(\$300)$

$\mathrm{EU}(g) = .80 \times u(\$400)$

$\mathrm{EU}(f') = .25 \times u(\$300) = .25 \times f$

$\mathrm{EU}(g') = .20 \times u(\$400) = .25 \times g$

Written in this manner, it is easy to see that the ratio of expected utilities of option *f'* to option *g'* in Decision 2 is identical to the ratio of expected utilities of options *f* to option *g* in Decision 1. Thus, mixing a 25% chance of *f* and *g* with a 75% chance of nothing should not affect which option has a higher expected utility and therefore which option is preferred. This violation of the independence axiom is known as the *common ratio effect.*

The typical intuition underlying modal preferences in the Allais example is that people are more sensitive to differences in probability near the ends of the [0, 1] probability scale than they are to similar differences in the middle of this scale. In Decision 1, people tend to be very sensitive to the distinction between a 100% chance of receiving a prize in option *f* and an 80% chance of receiving a slightly larger prize in option *g*. In contrast, in Decision 2, people are proportionally less sensitive to the distinction between a 25% chance of receiving a prize in option *f*' and a 20% chance of receiving a larger prize in option *g*'. More generally, the modal pattern of preferences discovered by Allais suggests that the impact of probabilities on the valuation of prospects is not linear.

***Challenge 2: The Reflection Effect and Fourfold Pattern of Risk Attitudes***

Kahneman and Tversky (1979) replicated Allais' original observations and expanded on them. To begin with, they documented the *reflection effect*: risk preferences for losses are typically the opposite of risk preferences for gains. For instance, most people prefer {gain $3,000 for sure} to {an 80% chance to gain $4,000 or else gain nothing}, thereby exhibiting risk aversion for gains, but they also prefer {an 80% chance to lose $4,000 or else lose nothing} to {lose $3,000 for sure}, thereby exhibiting risk seeking for losses.

When considering simple prospects of the form $\{x, p\}$ that offer a single gain or loss amount \$$x$ with a fixed probability $p$ (and otherwise nothing), Tversky and Kahneman (1992) observe a *fourfold pattern* of risk attitudes: risk aversion for moderate to high probability gains and low probability losses, coupled with risk seeking for low probability gains and moderate to high probability losses. This pattern is illustrated in Table 1. Each cell presents the median *certainty equivalent* (CE) of a prospect that offers $*x* with probability *p*. The certainty equivalent of a prospect is the sure amount that the individual finds equally attractive to receiving the risky prospect. For instance, in the lower-left cell we see that the certainty equivalent for a prospect that offers $100 with probability 95% is only $78, less than its expected value of $95, expressing risk aversion.

[Insert Table 1 about here.]

***Challenge 3: Rabin's paradox***

People typically exhibit pronounced risk aversion for mixed (gain-loss) gambles, even when the stakes are relatively small (see Table 2). For instance, Tversky and Kahneman's (1992) median participant found {a 50% chance to gain $102 or else lose $50} to be barely acceptable. Rabin (2000) provided a devastating argument against the notion that such risk aversion can be explained by a concave utility function. He proved that assuming the utility function to be increasing and concave in states of wealth, modest risk aversion for small-stakes gambles over all states of wealth implies an implausible degree of risk aversion for large-stakes gambles. For instance, someone who would always turn down {a 50% chance to lose $100 or else gain $110} must also turn down {a 50% chance to lose $1,000 or else gain an infinite amount of money}. The technical details of Rabin's calibration theorem are beyond the scope of this chapter but they come down to the fact that if one turns down the small-stakes gamble no matter one's level of wealth, then marginal utility would have to diminish quite rapidly—by way of analogy, if one could perceive the curvature of the earth by walking the length of a football field then the earth must be implausibly small.

[Insert Table 2 about here.]

## 2.2 Prospect Theory

The foregoing challenges can all be accommodated by prospect theory, the primary work for which Daniel Kahneman was awarded the 2002 Nobel Memorial Prize in Economic Sciences (Amos Tversky passed away in 1996 and was therefore not eligible to share the prize). We begin with a description of the original version of prospect theory (Kahneman & Tversky, 1979) and then will discuss the later, more technical update known as cumulative prospect theory (Tversky & Kahneman, 1992).

### *Composition Rule*

In prospect theory, the value (V) of a simple prospect that pays $\$x$ with probability $p$ is given by:

$$\mathrm{V}(x, p) = w(p)\, v(x)$$

where $w(\cdot)$ is the weighting function of outcome probabilities and $v(\cdot)$ is the value function for monetary gains and losses.

### *Properties of the Value Function*

The value function is characterized by three features that distinguish it from the treatment of utility in EU (see Figure 3). The first feature is *reference dependence*: value is a function of gains and losses relative to a reference point. Usually the status quo serves as the reference point for monetary outcomes, but the reference point is sometimes determined by a decision maker's goals (Heath, Larrick & Wu, 1999) or expectations (Kőszegi & Rabin, 2006). Moreover, decision makers may persist in maintaining past reference points, for instance viewing recent gains as "house money" (Thaler & Johnson, 1990).

The second feature of the value function is *reflection*: the value function exhibits diminishing sensitivity not only to increasing gains but also to increasing losses, so that its shape is concave for gains but convex for losses. This S-shape can partly explain the reflection effect mentioned above—it implies risk aversion for gains but risk seeking for losses, as illustrated in Figure 3. To see why the value function implies risk seeking for losses, note that if losing \$50 is more than half as painful as losing \$100, then one should prefer {a 50% chance to lose \$100 or else lose nothing} to {lose \$50 for sure}.

The third characteristic of the value function is *loss aversion*: the value function is steeper for losses than equivalent gains. This explains why people typically require more money to give up a possession (i.e., lose an object) than they would have paid to acquire it in the first place (i.e., when it was seen as a potential gain). In the context of risk, loss aversion explains why most people are risk averse for mixed gambles that offer a possibility of gaining or else losing money. For instance, most people would reject {a 50% chance to gain \$110 or else lose \$100} because the (negative) subjective value of losing \$100 is greater than the (positive) subjective value of gaining \$110. Typically, people require at least twice as much money on the "upside" of such a gamble as on the "downside" before they will accept it (e.g., {a 50% chance to gain \$200 or else lose \$100} is typically deemed barely acceptable). Loss aversion can explain behavior in Rabin's (2000) paradox, because it implies a kink (i.e., a discontinuity in the slope) in the value function that travels with the reference point so that a decision maker can exhibit pronounced risk aversion for small-stakes mixed (gain-loss) gambles and also exhibit a similar degree of risk aversion for large-stakes mixed gambles.

Figure 3 depicts a typical value function of the form:

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

with $\alpha$ ($\beta$) as parameters reflecting the degree of diminishing sensitive in the gain (loss) domain and $\lambda$ as the coefficient of loss aversion. Typically, $\alpha < 1$ indicates concavity in the domain of gains that is more pronounced as $\alpha$ decreases and $\beta < 1$ indicates convexity in the domain of losses that is more pronounced as $\beta$ decreases. Typically, $\lambda > 1$ indicates loss aversion that becomes more pronounced as $\lambda$ increases.

[Insert Figure 3 about here.]

***Properties of the Weighting Function***

The second major component of prospect theory that distinguishes it from expected utility is the probability weighting function, $w(\cdot)$, that represents the impact of probabilities on valuation of prospects (see Figure 4). The weighting function is normalized so that $w(0) = 0$ and $w(1) = 1$.

The weighting function is characterized by two commonly observed features. First, between two natural boundaries of impossibility and certainty, the weighting function exhibits *diminishing sensitivity* so that people are more sensitive to changes in probability near zero and near one than in the interior. Thus, a probability $r$ of winning a prize has more impact when added to probability zero than when added to intermediate probability $s$ (the *possibility effect*; $\Delta w_1 > \Delta w_2$ in Figure 4) and it has more impact when subtracted from probability one than when subtracted from intermediate probability $s + r$ (the *certainty effect*; $\Delta w_3 > \Delta w_2$ in Figure 4). Note that diminishing sensitivity of the weighting function away from certainty provides an explanation for the Allais paradox reviewed earlier. Second, the weights of complementary probabilities (i.e., $p$ and $1-p$) generally sum to less than one (suggesting an overall tendency toward risk aversion for gains and risk seeking for losses), a property known as *subcertainty*. Together, these properties give rise to an inverse-S-shaped function that overweights low probabilities, underweights moderate to large probabilities, and crosses the identity line below $p = .5$.

Figure 4 depicts a typical probability weighting function of the form:

$$w(p) = \frac{\delta p^{\gamma}}{\delta p^{\gamma} + (1-p)^{\gamma}},$$

where the parameter γ indexes the degree of curvature of the weighting function and δ indexes its overall elevation. Typically, $\gamma < 1$ indicates an inverse-S-shape that becomes more pronounced as γ decreases and $\delta < 1$ indicates subcertainty that becomes more pronounced as δ decreases. Note that prospect theory allows different shaped weighting functions for gains versus losses (thought the weighting function for losses is also generally assumed to be inverse-S-shaped).

An inverse-S-shaped weighting function reinforces the risk preferences implied by the value function for moderate to high probabilities, contributing to risk aversion for gains (because a moderate to high probability of gaining is discounted in the valuation of a prospect) and risk seeking for losses (because a moderate to high probability of losing is also discounted in the valuation of a prospect). However, the weighting function reverses the risk preferences implied by the value function for low probabilities, leading to risk seeking for low probability gains (because a low probability of gaining is overweighted) and risk aversion for low probability losses (because a low probability of losing is overweighted). Thus, it can explain the fourfold pattern of risk preferences, along with a range of empirical phenomena documented in numerous laboratory studies (Camerer & Ho, 1994; Gonzalez & Wu, 1999; Wakker, 2001; Wu & Gonzalez, 1996; 1998). Likewise, the tendency to overweight low probability events can explain the attraction of gambling on long-shots as in lotteries and horse races (e.g., Cook & Clotfelter, 1993; Jullien & Salanié, 2000; Snowberg & Wolfers, 2010; Thaler & Ziemba, 1988) as well as the attraction of insurance (Wakker, Thaler, & Tversky, 1997).

In sum, expected utility theory attempts to explain risk preferences using only the curvature of the utility function over states of wealth. In contrast, prospect theory explains risk preferences using a combination of three components: (a) the curvature of the value function over changes in wealth; (b) greater sensitivity to losses than equivalent gains; and (c) nonlinear probability weights. These elements explain the risk preferences characterized in Tables 1 and 2 as follows. The reason that most participants would reject {a 50% chance to gain $100 or else lose $50} (risk aversion for a mixed prospect) is that the absolute value of potentially losing $50 is more than the value of gaining $100 (loss aversion). The reason most participants would chose {gain $80 for sure} over {a 95% chance to gain $100 or else gain nothing} (risk aversion for a high probability gain) is that gaining $80 is more than 8/10 as attractive as gaining $100 (concavity of the value function for gains) and also a 95% chance feels like much less than a 100% chance (underweighting of high probabilities). The reason most participants would choose {a 95% chance to lose $100 or else lose nothing} over {lose $85 for sure} (risk seeking for a high probability loss) is because paying $85 is nearly as painful as paying $100 (convexity of the value function for losses) and also a 95% chance feels like much less than 100%. The reason most participants would choose {a 5% chance to gain $100 or else gain nothing} over {gain $10 for sure} (risk seeking for a low probability gain) is that a 5% chance feels like much more than no chance (overweighting of low probabilities)—and this tendency trumps the fact that $10 feels more than 1/10 as valuable as $100 (concavity of the value function for gains). Finally, the fact that most participants would rather {lose $5 for sure} than face {a 5% chance to lose $100 or else lose nothing} (risk aversion for a low probability loss) is because a 5% chance feels like much more than no chance, which trumps the fact that paying $5 is more than 1/20 as painful as paying $100 (convexity of the value function for losses).

A few points of common confusion are worth highlighting at this juncture. First, loss aversion is not the same as risk seeking for losses. Loss aversion reflects relative sensitivity of losses versus gains, whereas risk seeking for losses involves diminishing sensitivity to increasing losses. Thus, reluctance to accept 50-50 gambles that involve both gains and losses can be attributed to the fact that the value function is steeper for losses than gains (i.e., loss aversion). In contrast, the tendency to choose a moderate probability of losing money rather than lose its expected value for sure (i.e., risk seeking for losses) stems primarily from the convexity of the value function over losses. Second, decision weights are not generally interpreted as a measure of belief. Note that a decision maker considering the prospect {gain $100 if a fair coin lands heads} may weight the value of receiving $100 below .5, even though she believes that this event has precisely a 50% chance of occurring. Third, the concavity (convexity) of the value function is not the same as risk aversion (risk seeking), and overweighting low probability gains (losses) is not the same as risk seeking (risk aversion). Instead, risk preferences in prospect theory depend on the combined effect of the value function and the probability weighting function. As an example, a person might slightly overweight {a 10% chance to gain $100 or else gain nothing}, but nevertheless favor {gain $10 for sure} over this prospect because she finds $10 much more than 1/10 as attractive as $100 (in this case pronounced concavity of the value function trumps slight overweighting of a low probability).

### ***Framing, Editing, and Bracketing***

Expected utility theory and most normative models of decision under risk assume that preferences among prospects are a function of their impact on final states of wealth, and are not affected by variations in the way in which they are described—a principle known as *description invariance.* Prospect theory challenges this assumption by positing that preferences are influenced by how possible outcomes and their associated probabilities of occurrence are cognitively represented. There are three important implications.

First, representation can be influenced by the way in which prospects are *framed* or described, in terms of losses and gains and probabilities (Tversky & Kahneman, 1986). For instance, Tversky and Kahneman (1981, p. 453) presented participants with a problem in which there was an outbreak of an “unusual Asian disease, which is expected to kill 600 people” and then asked them to choose between a risky and a safe treatment program. When asked in a positive frame (choose between saving 200 people versus a 1/3 probability that 600 people will be saved and a 2/3 probability that no people will be saved) most respondents were risk averse. However, when presented the same options in a loss frame (choose between 400 people dying versus a 1/3 probability that nobody will die and a 2/3 probability that 600 will die) most respondents were risk seeking. Likewise, framing can influence probability weighting. For instance, when presented with a two-stage game in which there is a 75% chance that the game will end and a 25% chance to play a second stage that involves a choice between option *f* {gain $30 for sure} or option *g* {an 80% chance to gain $45 or else gain nothing} most respondents chose option *f*. However, when the same choice is presented as a single-stage game by multiplying the first stage probabilities through, most respondents favored option *g*’ {a 20% chance to gain $45 or else gain nothing} over option *f*’ {a 25% chance to gain $30 or else gain nothing}. This phenomenon, known as the *pseudo-certainty effect*, can explain, for example, why people are willing to pay a premium to eliminate an individual hazard rather than reduce multiple hazards by an equivalent amount (e.g., Viscusi, Magat, & Huber, 1987). For more on framing effects, see Chapter 27 of this volume.

Second, the original form of prospect theory assumed a number of editing operations that people apply to prospects to simplify them. For instance, people tend to round uneven numbers and reject options that are transparently dominated by others. While editing operations provide a psychologically plausible account of prospect representation that accommodates various decision patterns that are otherwise inconsistent with the rest of prospect theory, these operations are a weak part of the theory in that they are not precisely specified.

Third, preferences may vary as a function of how choices are grouped into sets, or *bracketed* (Read, Loewenstein, & Rabin, 1999). Choices are considered to be bracketed together when they are made by considering each choice concurrently with all other choices in the set. Generally, people tend to consider risky choices in isolation of other choice problems, which can lead several moderately risk averse decisions to collectively imply extreme risk aversion in the aggregate (Kahneman & Lovallo, 1993). However, when choices are bundled and feedback is pooled, people tend to be less risk averse. For instance, in one study participants choosing how much money, $x$, to bet on a gamble that offers {a 1/3 chance to lose $x$ or else a 2/3 chance to gain $2.5x$} bet more money when they received feedback on the outcomes of these choices less frequently compared to when they received such feedback more frequently (Gneezy & Potters, 1997). Choice bracketing can help explain various behavioral patterns observed in naturalistic data. For instance, Benartzi and Thaler (1995) show that the historically observed equity premium (i.e., the long-term outperformance of stocks over bonds) is consistent with investors who are loss averse and who evaluate their investments annually (i.e., who bracket their investment evaluation in one-year horizons), a behavioral pattern referred to as *myopic loss aversion*.

***Extensions to Uncertainty***

As mentioned earlier, theorists distinguish between decision under risk in which probabilities of outcomes are known precisely—as when making choices between simple gambles or in situations with well-known and stable long-term frequencies—and decision under uncertainty in which they are not. Naturally, applying risky choice models to naturalistic contexts requires one to understand how behavior changes when characteristics of prospects are not known precisely but must be assessed subjectively. A full account is beyond the scope of this chapter, but we sketch below a few important complications when one moves from risk to uncertainty.

**Cumulative Prospect Theory.** The original version of prospect theory (Kahneman & Tversky, 1979; henceforth OPT) applies to decisions under risk with at most two nonzero outcomes. Cumulative prospect theory (Tversky & Kahneman, 1992; henceforth CPT) extends this formulation from risk to uncertainty by conceptualizing the weights associated with outcomes as a function of events, including those with both known and unknown probabilities. Additionally, the inverse-S-shaped pattern of probability weighting is generalized as a property known as *bounded subadditivity* (Tversky & Fox, 1995; Tversky & Wakker, 1995). Finally, CPT accommodates any finite number of possible outcomes (and can be extended readily to accommodate continuous distributions).

CPT adopts the principle of *rank-dependence* in that the weight of any given outcome depends on the rank the outcome has in the ordering of all outcomes (i.e., its relative extremity). This feature eliminates some possible violations of stochastic dominance that could arise from the noncumulative probability weighting under OPT. For example, an individual with typical OPT-consistent preferences might be predicted to favor {a 10% chance to gain \$99 or else a 10%

chance to gain \$98 or else an 80% chance to gain nothing} to {a 20% chance to gain \$100 or else an 80% chance to gain nothing} because the overweighting of each of the 10% probabilities in the first prospect could more than make up for the slightly lower corresponding outcome valuations, despite the fact that the first option is dominated by the second. To eliminate this possibility, one of the editing operations in OPT is the notion that people eliminate options that are obviously dominated by other options (but see Tversky & Kahneman, 1986). Instead, CPT eliminates such a dominance violation—without the need for an ad hoc fix—through the calculus of rank-dependence.

To illustrate the rank-dependent composition rule of CPT, consider a prospect $\{x,p;y,q\}$ that offers \$$x$ with probability $p$ and \$$y$ with probability $q$ (and nothing otherwise). Under OPT, the outcome's value $v(x)$ is weighted by the outcome's probability weight $w(p)$. Rank-dependence under CPT, in contrast, weights the outcome's value by a decision weight $\pi(\cdot)$, calculated as the difference between the probability weight $w(\cdot)$ of obtaining an outcome at least as large as the focal outcome minus the probability weight $w(\cdot)$ of obtaining an outcome strictly larger than the focal outcome. Thus, under CPT: (1) outcome probabilities are cumulated in the order of the outcomes' rank positions from smallest gain (loss) to largest gain (loss); (2) these cumulative probabilities are then transformed into probability weights via $w(\cdot)$; and (3) these probability weights are then disaggregated into decumulative decision weights $\pi(\cdot)$.

More formally, the CPT valuation of a two-outcome prospect $\{x,p;y,q\}$ is given by:

$$\pi(x)\,v(x)+\pi(y)\,v(y)$$

with

$\pi(x) = w^{+}(p)$ and $\pi(y) = w^{-}(q)$ for mixed prospects, $x > 0 > y$,

$\pi(x) = w^{+}(p)$ and $\pi(y) = (w^{+}(q+p) - w^{+}(p))$ for pure gain prospects, $x > y \geq 0$,

$\pi(x) = w^{-}(p)$ and $\pi(y) = (w^{-}(q+p) - w^{-}(p))$ for pure loss prospects, $x < y \leq 0$.

For decision under risk involving two-outcome prospects and mixed (gain-loss) three-outcome prospects, the predictions of CPT coincide with those of OPT if one assumes $w^{+}(\cdot) = w^{-}(\cdot)$.

Finally, we note again that rank-dependent weighting eliminates the need for the editing phase of OPT. Returning to the foregoing example, note that in CPT the weight of a 20% chance to gain \$100 in the first prospect [$w^{+}(.2)$] is the same as the total weight afforded a 10% chance to gain \$99 [$w^{+}(.1)$] plus the weight afforded a 10% chance to gain \$98 [$w^{+}(.2) - w^{+}(.1)$]. Thus the CPT value of the latter prospect must be less than the CPT value of the former prospect for any monotonic value and weighting functions.

**The Two-Stage Model and Source-Preference.** The most natural extension of prospect theory to uncertainty replaces the objective probability $p$ with a judged probability $P(E)$, where $E$ is the natural event on which an outcome depends. In their two-stage model, Tversky and Fox (1995; see also Fox & See, 2003; Fox & Tversky, 1998; Wakker, 2004) propose that the value of a prospect that pays \$$x$ if event $E$ occurs (and nothing otherwise) is given by:

$$v(x)\, W(E) = v(x)\, w[P(\mathrm{E})],$$

where $w(\cdot)$ is the probability weighting function from prospect theory and $P(\cdot)$ is the judged probability that is assumed to satisfy support theory (Tversky & Koehler, 1994; Rottenstreich & Tversky, 1997), a behavioral model of judgment under uncertainty.

Support theory formulates judged probabilities as the ratio of evidential support that a decision maker can summon for a description of a focal event (e.g., precipitation in Chicago next April 1st) relative to a description of its complement (e.g., no precipitation in Chicago next April

1st). In support theory, breaking down an event into a more specific description (e.g., rain or sleet or snow or hail next April 1st in Chicago) generally increases its support and therefore judged probability. Thus, the model is *nonextensional*, allowing different descriptions of events to be assigned different judged probabilities. Moreover, separately evaluating these constituent events generally increases their support and therefore aggregate judged probability. Thus, more specific events are generally assigned higher judged probabilities on average than more inclusive events, and this tendency can amplify the tendency to overweight unlikely events and underweight likely events.

Although the two-stage model is simple and successful in predicting many choices under uncertainty, it must be extended to account for a second complication under uncertainty: *ambiguity aversion* (Ellsberg, 1961) which describes the reluctance to bet in situations where probabilities are vague rather than clear (see also Chapter 3). For instance, most people would rather bet on drawing a red (black) ball from an urn containing 50 red balls and 50 black balls than bet on drawing a red (black) ball from an urn containing 100 red and black balls in unknown proportion. More generally, decision makers exhibit *source preference* (Tversky & Fox, 1995; Tversky & Wakker, 1995; Abdellaoui, Baillon, Placido, & Wakker, 2011), favoring bets on some domains of uncertainty over others. Source preferences appear to reflect preferences to act in situations in which decision makers feel relatively knowledgeable or competent to situations where they feel relatively ignorant or uninformed (Heath & Tversky, 1991; Fox & Tversky, 1995; Fox & Weber, 2002). Source preferences can be modeled in prospect theory using weighting functions that are more elevated for more favored sources of uncertainty.

## 2.3 New Challenges

While prospect theory has been very successful in accounting for a range of empirical phenomena, there are a number of observations that challenge the general applicability if not some of the fundamental assumptions underlying prospect theory. Naturally, many of these observations also provide challenges for some alternative models of decision under risk as well. We review here the most important challenges that have been observed to date.

### ***Decisions from Description versus Experience***

Traditional paradigms for studying decision under risk and uncertainty involve *decisions from description* in which the probabilities and/or outcomes of prospects are fully described to the decision maker at the time of the decision. In contrast, in some newer paradigms investigating *decisions from experience*, the decision maker learns relevant characteristics of prospects by sampling (usually with replacement) from their respective outcome distributions, which are otherwise unknown to the decision maker. In this way, decisions from experience may resemble some naturalistic situations in which decision makers construct or adapt their mental representation of prospects as they interact with their environment.

Sampling error in decisions from experience may lead to decisions that on their surface appear to run counter to prospect theory. For instance, when people learn potential outcomes by observing returns of a financial investment over time or consequences of not locking a car door on multiple occasions, they may fail to sample an unlikely outcome that is theoretically possible (e.g., a sudden crash in the stock market or the car being stolen), and therefore “underreact” to that possibility, as if “underweighting” the true outcome probability (Hertwig, Barron, Weber, & Erev, 2004; Fox & Hadar, 2006). Even when the sample of outcomes is carefully observed and representative of the underlying “true” probability distribution, decisions from experience appear to reflect less overweighting of low probabilities than is generally assumed in prospect theory analysis (Ungemach, Chater, & Stewart, 2009).

The differences in behavior observed across decisions from description and decisions from experience are referred to as the *description-experience gap*. This gap might be accommodated within a prospect theory framework by allowing variations in the elevation and curvature of the probability weighting function across decision paradigms. In particular, there is evidence that decision makers exhibit less elevated probability weighting functions when comparing sampled (uncertain) prospects to fully described (risky) prospects, perhaps capturing ambiguity aversion (Abdellauoi, l'Haridon, & Paraschiv, 2011). Moreover, decision makers appear to exhibit more linear probability weighting in decisions from experience (with no sampling error) than corresponding decisions from description, perhaps capturing a tendency to better apprehend extreme probabilities when they are "unpacked" into events that are sampled in proportion to their probability of occurrence (Fox, Long, Hadar, & Erner, 2014).

For further discussion of decisions from experience, see Chapter 10 in this volume and the reviews by Hertwig and Erev (2009) and de Palma, Abdellaoui, Attanasi, Ben-Akiva, Erev, Fehr-Duda, Fok, Fox, Hertwig, Picard, Wakker, Walker, and Weber (2014).

***Invariance Violations***

Most normative theories of choice implicitly assume that preferences are invariant to the way that options are described (*description invariance*), the procedure by which they are elicited (*procedure invariance*), and the context of irrelevant alternatives in the choice set (*context independence*; Tversky, 1996). Framing effects pertaining to the representation of gambles violate description invariance and are explicitly accommodated by prospect theory. It is generally assumed that decision makers tend to adopt frames that are implied by the formulation of a decision problem (i.e., the description of alternatives)—but that frames are also influenced partly by "norms, habits, and personal characteristics of the decision maker" (Tversky & Kahneman, 1981). Other violations of description invariance, such as the tendency to be more risk averse when considering purchasing "insurance" against a risky loss than when choosing between a sure payment and a risky loss without the "insurance" label (Hershey, Kunreuther, & Schoemaker, 1982) are not accommodated readily by prospect theory.

Prospect theory is intended as a theory of choice between prospects and is therefore not designed to accommodate other modes of eliciting preferences (such as measuring willingness to pay for each prospect) that may give rise to violations of procedure invariance. For example, it is well known that people tend to attach a higher *price* to low-probability high-outcome prospects (e.g., {a 31% chance to gain $16 or else gain nothing}) than they do to high-probability low-outcome prospects of similar expected value (e.g., {a 97% chance to gain $4 or else gain nothing}), even though they tend to *choose* higher-probability options (Tversky, Slovic, & Kahneman, 1990). This *preference reversal* phenomenon appears to result from the particular elicitation mode (pricing versus choice) facilitating greater weight to the attribute that is most compatible with that elicitation mode—thus, people tend to give more weight to dollar outcomes when pricing prospects, whereas they tend to give more weight to probabilities of realizing outcomes when choosing between prospects. It is worth mentioning that many applications of prospect theory and other decision theories interpolate prices (such as certainty equivalents) from a series of choices rather than a direct pricing tasks. For instance, if a decision maker prefers {a 50% chance to gain $100 or else gain nothing} to {gain $38 for sure}, but he prefers {gain $40 for sure} to the risky prospect, then one might infer his certainty equivalent to be roughly $39. This said, if researchers use such a *multiple price list* method (e.g., Andersen, Harrison, Lau, &

Rutström, 2006) in which participants choose between the prospect to be priced and a series of decreasing sure amounts, after several trials participants may come to simplify the task by directly assessing a price for the prospect, and then quickly filling out the series of choices to reflect this price (Fischer, Carmon, Ariely, & Zauberman, 1999). To the extent that this occurs, price measurement may be biased as in the preference reversal phenomenon discussed above. A fuller account of methodological issues in eliciting prospect theory preferences is beyond the scope of this chapter but can be found in Fox and Poldrack (2014, pp. 550-557).

Context independence can be violated in an environment where people have difficulty deciding and therefore seek reasons to justify choosing a particular option, thereby bypassing complicated evaluation that is captured by integration models (Shafir, Simonson, & Tversky, 1993). For instance, most people have difficulty choosing between option *f* {a 40% chance to gain $25 or else gain nothing} and option *g* {a 30% chance to gain $33 or else gain nothing}. However, when a decoy option, option *f'* {a 40% chance to gain $20 or else gain nothing} is added to the choice set that is asymmetrically dominated by option *f,* people are more likely to favor option *f*; however, when a different decoy option option *g*' {a 30% chance to gain $30 or else gain nothing} is added to the option set that is asymmetrically dominated by option *g*, people are more likely to favor option *g* (e.g., Wedell, 1991; see also Huber, Payne, & Puto, 1982). Violations of context independence, like violations of procedure invariance, are not accommodated readily by prospect theory.

### *Internality Violations*

One implicit assumption of most integration models of decision under risk, including prospect theory, is the *internality axiom*, which states that the value of a prospect must lie between the lowest and highest possible outcome that the risky prospect offers. A striking violation of this axiom was documented by Gneezy, List, and Wu (2006), and is known as the *uncertainty effect*. In one study, participants who were offered a $50 *Barnes & Noble* gift certificate were willing to pay a median of $25; another group of participants who were offered a $100 gift certificate were willing to pay a median of $40. Thus, under internality, participants should be willing to pay somewhere between $25 and $40 for a lottery that offers a 50-50 chance of receiving a $50 gift certificate or else a $100 gift certificate. Remarkably, participants offered such a lottery were willing to pay a median of only $5.

Subsequent studies have had mixed success establishing the robustness of the uncertainty effect. Keren and Willemsen (2009) conclude that the effect diminishes after excluding inattentive participants. However, Simonsohn (2009) replicated the pattern, attributing the uncertainty effect to *direct risk aversion*, the notion that decision makers experience a direct disutility when facing uncertainty. Other researchers provide evidence suggesting that the effect may be an artifact stemming from different framings between the conditions, e.g., framing the risky option as a “lottery of gift certificates” versus a “risky gift certificate” may make a difference (Rydval, Ortmann, Prokosheva, & Hertwig, 2009; Yang, Vosgerau, & Loewenstein, 2013). On the other hand, Newman and Mochon (2012) find that the uncertainty effect is robust to various framings. It appears that additional research is needed to achieve consensus on this provocative phenomenon.

### ***Violations of Gain-Loss Separability***

As mentioned, one cornerstone of prospect theory is the notion that prospects are evaluated relative to some reference point that distinguishes losses from gains. In CPT, mixed prospects, i.e., prospects that entail both gains and losses as possible outcomes, are valued by simply summing the gain component and the loss component, which are valued independently of each other. This principle is known as *gain-loss separability* and is also assumed when measuring loss aversion. A systematic violation of the "double-matching" axiom that underlies gain-loss separability was documented by Wu and Markle (2008). In particular, they document situations where participants prefer mixed gamble *f* to mixed gamble *g* but prefer the gain portion of *g* to *f* and also the loss portion of *g* to *f*. The authors attribute this phenomenon to more pronounced probability weighting distortions for mixed prospects than gain-only or loss-only prospects. Birnbaum and Bahra (2007) confirm the findings of Wu and Markle (2008) and add that their *transfer of attention exchange (TAX) model* is able to accommodate violations of gain-loss separability. More recently, Por and Budescu (2013) report that violations of gain-loss separability are robust to variations in experimental stimuli.

### ***Violations of Coalescing***

One important feature of CPT is *coalescing,* the notion that two branches of a prospect that have the same outcome are treated as a single branch bearing the aggregate probability (this is also an editing feature of OPT). Birnbaum (2008a) reviews empirical challenges to coalescing among other prospect theory assumptions. For instance, consider a pair of prospects that pay various amounts of money if a particular marble is drawn from an urn. Prospect *f* offers {85 red marbles to gain $100 and 10 white marbles to gain $50 and 5 blue marbles to gain $50} while prospect *g* offers {85 black marbles to gain $100 and 10 yellow marbles to gain $100 and 5 purple marbles to gain $7}. Under prospect theory's assumption of coalescing, one would assume that the first prospect would be represented as {an 85% chance to gain $100 or else a 15% chance to gain $50} while the second prospect would be represented as {a 95% chance to gain $100 or else a 5% chance to gain $7}. If so, a participant choosing *f* over *g* (as predicted by median parameters from Tversky & Kahneman, 1992) should also choose a gamble *f*' that offers

{85 black marbles to gain \$100 and 15 yellow marbles to gain \$50} over gamble *g*' that offers {95 red marbles to gain \$100 and 5 white marbles to gain \$7}. Strikingly, most participants in a study by Birnbaum (2004) preferred *f* to *g* but most preferred *g*' to *f*', the modal within-participant pattern. Birnbaum (2008a) advances alternative models that can accommodate this finding, which we review in Section 3 below.

***Violations of Probability-Outcome Independence***

*Probability-Outcome independence* refers to the valuation principle that the probabilities and the outcomes of a prospect independently contribute to a prospect's value. Both expected utility theory and the original form of prospect theory invoke this principle through their composition rules that segregate probabilities and decision weights from utilities or subjective values. Recall that cumulative prospect theory assigns decision weights according to the probabilities of cumulative outcomes, so that in some sense this model builds in a form of probability-outcome dependence for prospects having more than one positive or negative possible outcome.

Rottenstreich and Hsee (2001) document a striking violation of probability-outcome independence by showing that participants exhibit more pronounced diminishing sensitivity to probabilities for relatively affect-rich outcomes (e.g., a kiss from a favorite movie star or an electrical shock) than relatively affect-poor outcomes (a simple monetary gain or loss). McGraw, Shafir, and Todorov (2010) attributed these results to a more general difference in probability sensitivity when evaluating monetary versus nonmonetary outcomes. They documented decreased probability sensitivity for nonmonetary outcomes that were, in fact, deemed *less* affect-rich than corresponding monetary outcomes (e.g., spend four hours entering data).

## 3. Alternative Behavioral Models of Risky Choice

While prospect theory has been the most popular behavioral model of risky choice to date, the foregoing section highlights a number of empirical phenomena that cannot be accommodated without modification to the original framework. In addition, several alternative models have been proposed to accommodate some subset of apparent empirical violations of prospect theory, derive choices from different primitives, and/or formalize alternative psychological processes. Below we briefly review a variety of alternative models that represent the range of distinct approaches that researchers have taken: risk-value models, alternative integration models, heuristic models, and process models.

### 3.1 Risk-Value Models

Some approaches to modeling decision under risk have taken a measure of riskiness as the primitive from which preferences are directly mapped. The most prominent such model is the *mean-variance model* that originated in financial decision theory (Markowitz, 1952) and conceives of preferences as a function of: (a) risk, operationalized as variance in the probability distribution over possible outcomes (e.g., returns of an asset), $\sigma$, and (b) expected value, operationalized as the mean of that distribution, $\mu$. Functions of these two variables define indifference curves reflecting assets (or portfolios of assets) that a person considers equally attractive. It is worth mentioning that under particular assumptions, for example a quadratic utility function or normally distributed returns, expected utility theory and the mean-variance model coincide. The mean-variance model also serves as the foundation for the Capital Asset Pricing Model (CAPM; Sharpe, 1964) according to which the expected return to an asset is a function of how the asset's returns move with general market returns. Specifically, the CAPM beta factor represents the relative co-movement of the asset with the market as expressed by the ratio of the covariance of the asset's returns with the market returns over the variance of the market returns.

A separate stream of risk-value approaches has emerged from research in behavioral decision theory in which researchers have found the perceived riskiness of prospects to be influenced by factors other than variance. Holding variance fixed: (1) adding a constant positive amount to all possible outcomes makes the distribution appear less risky; (2) perception of riskiness is more sensitive to outcomes perceived as losses than those perceived as gains; and (3) perception of riskiness tends to be higher for negatively skewed than positively skewed distributions. Various specifications of risk-value models have been proposed that take these observed differences in perceived riskiness into account (e.g., Jia, Dyer, & Butler, 1999; Pollatsek & Tversky, 1970; Sarin & Weber, 1993; Weber & Milliman, 1997).

### 3.2 Integration Models

As previously stated, expected utility theory and prospect theory are both instances of *integration models*, conceiving choices as some function of probabilities multiplied by some function of outcomes. Several additional integration models have been proposed in the last few decades. A first class of alternative integration models is based on the notion that the decision maker considers counterfactual outcomes when valuing prospects. In some models decision makers compare possible focal outcomes with corresponding outcomes of alternative prospects (i.e., counterfactual thinking is between-prospect). A prominent example is *regret theory* (Bell, 1982; Loomes & Sugden, 1982). In other models decision makers compare possible focal outcomes with alternative outcomes of the prospect under consideration (i.e., counterfactual thinking is within-prospect). Examples include *disappointment theory* (Bell, 1985; Loomes & Sugden, 1986), *disappointment aversion theory* (Gul, 1991), and *decision affect theory* (Mellers, Schwartz, Ho, & Ritov, 1997). A second class of alternative integration models introduce distinct valuation paradigms, notably: *salience theory* (Bordalo, Gennaioli, & Shleifer, 2012), *security-potential/aspiration (SP/A) theory* (Lopes, 1987), and *configural weight models* (Birnbaum, 1974). We discuss all of these models in greater detail below.

*Regret theory* (Bell, 1982; Loomes & Sugden, 1982) notes that when choosing among multiple options, a decision maker always rejects at least one alternative. Depending on which state of the world obtains, the decision maker might regret foregoing an alternative that would have yielded a superior outcome or rejoice at having avoided picking an alternative that would have yielded an inferior outcome. Thus, regret theory includes both a pure utility associated with potential outcomes and a regret or rejoicing function of the difference in outcomes between the selected and the foregone option.

*Disappointment theory* (Bell, 1985; Loomes & Sugden, 1986) considers valuation stemming from the comparison of outcomes in alternate states of the world, within the same prospect. Considering a prospect with two positive outcomes, the decision maker will experience disappointment if the smaller outcome is realized and elation if the larger outcome is realized. The strength of disappointment and elation can vary within an individual.

*Disappointment aversion theory* (Gul, 1991) postulates that the decision maker considers outcomes relative to the overall subjective value of a prospect. Thus, this model decomposes alternatives into two sub-prospects: an elation component and a disappointment component. The elation (disappointment) component contains the outcomes that are greater or equal to (smaller or equal to) the certainty equivalent of the full prospect. Both components are then weighted by the respective probabilities that one of their outcomes obtains. Disappointment aversion is introduced as a parameter reflecting the degree to which these probabilities are transformed.

Specifically, the probability of obtaining an outcome from the disappointment component is overweighted (underweighted) if the individual is disappointment averse (elation loving). While the original form of disappointment aversion theory was designed to offer an alternative account for behavior observed in the Allais paradox, this framework has more recently been extended to model equilibrium asset prices in economies where the representative agent exhibits generalized disappointment averse preferences (e.g., Routledge & Zin, 2010).

*Decision affect theory* (Mellers, Schwartz, Ho, & Ritov, 1997) assumes that decision makers choose to maximize the anticipated affective response to the selected option, where affective response is driven by the difference between the obtained outcome and a counterfactual outcome, and is amplified when an outcome is more unexpected.

*Salience theory* (Bordalo, Gennaioli, & Shleifer, 2012) is another context-dependent approach to valuation, in which decision weights are a function of the salience of associated payoffs (i.e., how much they attract decision makers' attention). Salience of a state is assumed to increase with the degree to which outcomes differ between two alternatives if that state obtains. For instance, when choosing between {gain $2,400 for sure} or {a 66% chance to gain $2,400, a 33% chance to gain $2,500, or else a 1% chance to gain nothing}, individuals tend to be risk averse and prefer the sure amount over the risky option. Salience theory postulates that the difference in the minimum possible outcome ($2,400 vs. $0) is more salient than the difference in the maximum possible outcome ($2,400 vs. $2,500), prompting *local thinking* focused on the low outcome, which in turn triggers risk averse behavior. The authors provide empirical evidence that salience theory can explain common paradoxes, such as the Allais paradox and the preference reversals that can be observed when varying the elicitation mode between choosing and pricing.

*Security-potential/aspiration (SP/A) theory* (Lopes, 1987) breaks down the valuation of a prospect into two psychologically distinct criteria: the security-potential criterion (SP) and the aspiration criterion (A). The security-minded analysis (S) focuses on the decumulative probability that an outcome at least as good as the considered outcome will be realized, while the potential-minded analysis (P) focuses on the probability that a strictly better outcome will be realized. Separately, the decision maker considers the probability that a particular aspiration level will be achieved or exceeded (A). The utility of a prospect is a function of the SP and A components of the valuation. Lopes and Oden (1999) provide an empirical comparison of CPT and SP/A theory in explaining observed within- and between-subject data and find that SP/A theory better fits the choice patterns in their data (see also Rieger, 2010). Moreover, Payne (2005) presents evidence that decision makers are sensitive not only to probabilities of individual outcomes but also to the overall probability of gaining (or avoiding losing) and suggests that this is in line with the aspiration level concept of SP/A theory. Additionally, SP/A theory has informed the development of a behavioral portfolio theory (Shefrin & Statman, 2000).

*Configural weight models* (Birnbaum, 1974) constitute another group of alternative rank-dependent models. One of the most prominent configural weight models is the transfer of attention exchange model (TAX; see Birnbaum & Chavez, 1997; Birnbaum & Navarrete, 1998) that interprets lotteries as “trees with branches” (Birnbaum, 2008a, p. 464) rather than as probability distributions over outcomes. The idea behind this metaphor is that every branch (i.e., consequence or state of the world) of a decision situation is relevant for its valuation. For example, if there are two states of the world that happen to yield the same outcome, the TAX model would treat them as two separate branches. In contrast, as previously mentioned, CPT assumes that these two branches would be coalesced into one consequence with the shared outcome and the summed probability. Under the TAX model, branches are assigned decision weights that depend on the "attention" that the decision maker allocates to a particular branch, which depends on the degree of risk aversion the decision maker exhibits. Thus, a risk averse individual affords more attention to lower outcome branches, thereby transferring attention from high outcome branches to low outcome branches (Birnbaum, 1999, Birnbaum, 2008a). A second configural weight model is the rank affected multiplicative model (RAM; Birnbaum, 2005) in which decision weights are a multiplicative function of a branch's probability and rank. Empirical support for TAX and RAM is found in indirect tests that illustrate violations of CPT assumptions such as coalescing (e.g., Starmer & Sugden, 1993; Birnbaum, 2008a) and direct tests that compare the two models with CPT (e.g., Birnbaum, 2005; Marley & Luce, 2005).

### 3.3 Heuristic Models

Heuristic models, unlike integration models, do not account for all attributes of prospects simultaneously. Instead they focus on selective information to simplify decisions. Several choice heuristics have been proposed, many of which have been applied to riskless multiattribute decisions, while others have also been applied to risky decisions (see Gigerenzer & Gaissmaier, 2011 and Payne, Bettman, & Johnson, 1993 for overviews).

The most noteworthy risky choice heuristic that has been advanced in recent years is the *priority heuristic* (Brandstätter, Gigerenzer, & Hertwig, 2006), which is a lexicographic rule that ranks options according to a hierarchy of reasons. The priority heuristic represents the sequence of priorities that a decision maker may evaluate when choosing among two prospects: first to maximize the minimum gain; second to maximize the probability of the minimum gain; third to maximize the maximum possible gain. Additionally, the priority heuristic introduces a stopping rule in the form of aspiration levels that trigger a decision. For instance, if the difference in minimum gain is greater than the aspiration level (1/10 of the maximum gain), then the prospect with the larger minimum gain is chosen. If the difference is below this threshold, then the decision maker moves on to the next priority and compares probabilities for the minimum gain. If the difference is greater than the aspiration level (1/10 of the probability scale), then the prospect with the larger probability for the minimum gain is chosen. If the difference is below this threshold, then the decision maker moves on to the next priority and choses the prospect with the higher maximum gain. Importantly, decisions are always made based on one reason only, and there are no trade-offs between attributes.

Brandstätter, Gigerenzer, and Hertwig (2006) show that the priority heuristic can accommodate well-known decision phenomena such as the Allais paradox and can predict modal choices among a particular set of prospects in their validation set. However, the model fares less well when one examines different choice sets from those initially examined by Brandstätter, Gigerenzer, and Hertwig (2006), or if one allows competing decision models to account for individual-level heterogeneity (Birnbaum, 2008b; Glöckner & Betsch, 2008; Glöckner & Pachur, 2012; Rieger & Wang, 2008). Moreover, the priority heuristic has been criticized for providing a model of processes underlying choice that has not been supported by empirical data (Glöckner & Herbold, 2011; Hilbig, 2008; Johnson, Schulte-Mecklenbeck, & Willemsen, 2008).

### 3.4 Process Models

Integration models, risk-value models, and even heuristic models of decision under risk are typically construed to be "as-if" models, representing choice behavior as if the individual acts according to the articulated decision principle (e.g., maximizing expected utility). Process models, in contrast, attempt to explicitly model the cognitive process underlying a decision. Empirical support for such process accounts often tentails supplementing decision data with process tracing data, which can be obtained, for example, through eye-tracking methods, think-aloud protocols, and response latencies (Brandstätter & Gussmack, 2013; Schulte-Mecklenbeck, Kühberger, & Ranyard, 2011).

One of the best known process models of decision under uncertainty is *decision field theory* (Busemeyer & Townsend, 1993; Busemeyer & Diederich, 2002), a diffusion model that describes a Markov random walk process for the relation between the accumulation of preference for one prospect over another and deliberation time. A decision is made once a particular threshold of accumulated preference is reached. Studies using eye-tracking techniques generally support the process predictions made by decision field theory (Fiedler & Glöckner, 2012; Glöckner & Herbold, 2011).

A second prominent process approach is *fuzzy-trace theory* (Reyna & Brainerd, 1995; for an overview see Reyna 2004), which posits that people encode two types of representations of prospects: verbatim traces and gist traces. Verbatim traces are exact representations of prospects (e.g., the probability distribution over possible outcomes) that rapidly fade from memory; whereas gist traces are fuzzy representations of qualitative features of prospects that remain accessible over time. According to fuzzy-trace theory decision makers rely on gist traces where possible when making decision. For instance, a person might recall gist information that "prospect A does not entail any losses but prospect B does," and choose A accordingly. Fuzzy-trace theory has been successful in explaining a number of risky choice phenomena such as simple framing effects (e.g., Kühberger & Tanner, 2010).

## 4. From the Lab to the Field

Having surveyed a number of behavioral models of decision under risk, the question arises how insights from laboratory research using simple chance gambles can be extended to understand and predict naturalistic risk taking behavior. A few differences between laboratory studies and field behaviors immediately come to mind. To begin with, laboratory experiments on which many of the foregoing models are based are mostly conducted using simple static chance gambles, whereas naturalistic decisions typically involve complex contingencies that are extended over time; for instance, most investment decisions have such complex and dynamic characters. Second, most laboratory studies of risk taking involve monetary gambles, whereas naturalistic decisions may occur in a variety of domains; for instance, a decision maker's risk tolerance when choosing among chance gambles may or may not predict behavior when driving. Third, most laboratory stimuli involve choices among antiseptic contingencies, usually involving monetary outcomes, whereas naturalistic decisions often involve contingencies that are emotionally resonant and laden with personal (and social) meaning; for example, considering whether or not to administer a vaccine to a child can trigger a host of feelings and broader reflection. Finally, we note that only a subset of laboratory studies involve real financial incentives, whereas by definition naturalistic decisions always have real consequences. To adequately predict naturalistic decision behavior using models developed and tested in the laboratory, one ought to take these factors into account.

Keeping these distinctions in mind, we next develop a conceptual framework for extending insights from the laboratory to the field, as illustrated in Figure 5. Building a model of behavior in a naturalistic environment entails three steps. The first step is to determine the appropriate *baseline model* for predicting behavior, which may be influenced by a host of factors including decision makers' subjective construal of the decision situation they find themselves in. For instance, an environment that involves a simple discrete choice such as whether to purchase a lottery ticket may tend to be viewed as a simple chance gamble and therefore lend itself to modeling using prospect theory. The second step is to determine the relevant *model variables* to which the baseline model is applied, which is presumably determined by the decision maker's cognitive representation of acts, states, and consequences. For instance, to apply prospect theory one must determine the reference point, the relevant outcomes and probabilities, and so forth. The third step is to determine the relevant *model parameters* governing the application of the baseline model to the relevant variables, which will be determined by a variety of factors that contribute to risk preferences. For instance, in prospect theory modeling there are parameters governing the shapes of the value and weighting functions.

Each step in building a predictive model can be analyzed at multiple levels. We can examine *typical behavior* in the general population, *individual differences* (or subgroup differences) that vary systematically from that central tendency, and behavior at a particular moment in time that may vary systematically around an individual's (or group's) central tendency, perhaps as a function of decision makers' cognitive, affective, and/or motivational states (*state differences*). Each successive level of analysis can potentially explain additional variance in an individual's naturalistic risk taking behavior, and different analytical goals may suggest pursuing this framework to different levels of analysis. For instance, a financial services company considering introducing a new investment opportunity might be interested in only the first level of analysis (typical behavior) to predict aggregate market demand for the product. In contrast, a marketer at the aforementioned firm might proceed to the second level (individual differences) in order to evaluate how she can best market various products to different market segments. Finally, a financial advisor trying to provide responsible guidance to an individual client concerning whether or not to purchase such investments may want to proceed all the way to the third level (state differences) to understand the impact the client's current emotional and motivational states on the current expression of her risk preferences.

We next examine our framework in some detail, considering each step of building a predictive model (baseline model, model variables, model parameters) at each level of analysis (typical behavior, individual differences, state differences).

[Insert Figure 5 about here.]

***Step 1: Baseline Model***

In order to apply insights from laboratory research to naturalistic settings we must first select a baseline model that captures behavior of representative decision makers. While we believe that prospect theory can provide an excellent starting point in many situations it is fair to assume that other models will better predict behavior in some contexts. We assert that the choice of an appropriate model should take into account the way in which decision makers construe the decision situation in question. Naturally, there is no formal procedure for deciding which model applies best under which circumstances, but we can begin to sketch out some preliminary guidelines.

A natural starting point for determining the appropriate model of risk taking behavior is to consider the complexity of the given decision task. For instance, a decision maker's thought process when choosing between $300 for sure versus $1,000 if a fair coin lands heads (and nothing otherwise) may be qualitatively distinct from her thought process when choosing between investing $300 in U.S. Treasury Bills versus a similar amount in stocks. While the coin bet could generally be construed as a choice between a two-outcome gamble and a sure thing, potentially suggesting prospect theory as the baseline model, the investment decision might be construed as involving a normal probability distributions over potential returns, suggesting a risk-value model such as mean-variance, in which the complexity of the distribution is reduced to its first two moments. Note that such a simplification may ignore relevant features of the environment such as the “fat tails” that characterizes many empirical investment outcome distributions, giving rise to a prediction that decision makers will often neglect the possibility of “black swan” events in their decision making (Taleb, 2007).

Moving from the simple coin toss to a more complex gamble with several nonzero outcomes, decision makers may simplify the task by focusing on the overall probabilities of winning or losing (Payne, 2005), calling for a model that accounts for aspirations, such as SP/A theory (Lopes, 1987). Similarly, a complex investment scenario might be construed in a simplified manner, partitioned into mental accounts that are each considered independently. For one mental account, investors aspire not to lose the entire investment (resulting in a less risky asset allocation within this account), whereas for the other mental account, investors aspire to high returns (resulting in a more risky asset allocation within this account). This approach, taken by the behavioral portfolio theory, coincides with the empirical observation that typical decision makers simultaneously exhibit risk aversion and risk seeking by purchasing insurance policies and lottery tickets at the same time (Shefrin & Statman, 2000).

More generally, there is ample evidence that complex decision situations can lead typical decision makers to rely on simplifying choice heuristics that require less effort and information processing capacity than do more integrative approaches (Payne, Bettman, & Johnson, 1993). One such effort-reducing strategy is the *affect heuristic* in which general feelings of “goodness” or “badness” about a risky option drive decisions (Finucane, Alhakami, Slovic, & Johnson, 2000). Some researchers have suggested that as complexity increases, people may be more likely to employ the affect heuristic in risky choice (Slovic, Finucane, Peters, & MacGregor, 2007).

Another aspect to consider in selecting a baseline model is the nature of the outcomes and probabilities. In some risky situations decision makers may not construe situations as risky at all, neglecting probabilities and instead focusing only on the outcomes, limiting the applicability of probabilistic integration models such as prospect theory. Rottenstreich and Kivetz (2006) identify three types of decision situations that give rise to what they call “probability neglect”: (a) scenario or story construction; (b) role-based considerations; and (c) appeals to social norms. Some situations may guide particular decision makers to construct nonprobabilistic scenarios or stories to guide their choices. For instance, studies of experienced executives have found that they tend to resist thinking about risky choices (e.g., whether or not to undertake a merger) as gambles requiring assessments of outcome probabilities, but instead construe these situations as challenges to be overcome (March & Shapira, 1987). Role-based considerations may guide choices under risk when a decision maker’s social role dictates a particular behavior. For instance, a doctor may feel obligated to treat a patient in a crisis without assessing probabilities over possible outcomes of this treatment or considering the opportunity costs of treating the current patient rather than others who are in urgent need of care (Weber, Ames, & Blais, 2005). Finally, consideration of social norms (e.g., those pertaining to procedural fairness or morality) can sometimes override probabilistic considerations. For example, people are often unwilling to trade off protected values (i.e., values arising from deontological rules) for economic values. Thus, an environmentally conscious fisherman might oppose fishing in waters that are sometimes inhabited by dolphins, without actively considering the probability that dolphins would be harmed (Baron & Spranca, 1997).

Turning from typical decision makers' construal of the decision situation to individual differences, the selection of a baseline model could also depend on characteristics of the target population. Specifically, different populations are likely to exhibit different levels of sophistication, and may therefore rely on different decision strategies. For instance, Fox, Rogers, and Tversky (1996) found that professional option traders, who are well schooled in the calculus of chance, and whose core job entails assessing probability distributions on a daily basis, tended to price risky prospects by their expected value, as if they were following a fixed decision rule. Interestingly, it is not necessarily the case that greater sophistication leads to greater consistency in decision making. For instance, Reyna and Ellis (1994) found that fifth graders were substantially more apt to shift their risk preferences across gain/loss frames than were preschoolers when choosing between a simple chance gamble and a sure thing. While this pattern seems to contradict the natural intuition that older children engage in more computational thinking, it accords with the notion from fuzzy-trace theory (Reyna & Brainerd, 1995) that children transition as they age from verbatim representations (that promote quantitative thinking to the limits of their ability) to gist-based representations (that promote qualitative thinking and encode valences of outcomes). In this case, the gist representation might prompt participants to favor a prospect that offers "a sure gain of something" over "a possible gain of something" in the gain frame but favor a prospect that offers "a possible loss of something" over "a sure loss of something" in the loss frame.

Of course, decision makers may switch their decision strategies based on their current emotional, motivational, and/or cognitive states, calling for different predictive models under those conditions. For instance, Whitney, Rinehart, and Hinson (2008) found that putting participants under cognitive load by having them remember long strings of digits drove greater reliance on the affect heuristic and also reduced the impact of framing effects. Likewise, time pressure has been found to increase reliance on the affect heuristic, in part due to reduced availability of cognitive resources (Finucane, Alhakami, Slovic, & Johnson, 2000).

We close this section by noting that one need not restrict the scope of analysis to a single model that best characterizes a representative decision maker's behavior, but can rather apply combinations of different models in order to characterize heterogeneity present in many naturalistic applications. The idea of *mixture models* is to simultaneously consider multiple decision models and represent the overall model prediction as some weighted average of the individual models. A decision analyst can specify the level on which the focal model can vary. For instance, when using a combination of expected utility theory and prospect theory to predict choices between gambles, the best predictive model might be allowed to vary across individual decisions (i.e., some choices are better predicted by expected utility theory, whereas other choices are better predicted by prospect theory; e.g., Harrison & Rutström, 2009) or individual participants (i.e., some participants' choices are better characterized by expected utility theory, whereas other participants' choices are better characterized by prospect theory; e.g., Bruhin, Fehr-Duda, & Epper, 2010).

For the purposes of illustrating steps 2 and 3 of the present analytical framework, we will generally assume prospect theory as our baseline model. To our reading, prospect theory, despite the aforementioned challenges and documented violations, remains the most broadly descriptively valid model that has been advanced to date. A full account of the naturalistic phenomena that prospect theory accommodates is beyond the scope of this chapter but we highlight a few examples that are relevant to risky choice. The reflection effect has been linked to the empirical observation that investors are generally more willing to sell investments when they are worth more than the original purchase price than when they are worth less, a phenomenon known as the *disposition effect* (Shefrin & Statman, 1985; Odean, 1998). Loss aversion, coupled with the tendency to review returns on investments over short time horizons, has been used to explain the tendency for even long-term investors to demand a large premium for investing in stocks rather than fixed-income investments (Benartzi & Thaler, 1995). As for probability weighting distortions, prospect theory can explain: (i) why lotteries become more attractive as the top prize increases, even as the probability of winning decreases proportionally (Cook & Clotfelter, 1993), (ii) the attractiveness of speculative investments such as initial public offerings with positively skewed probability distributions over possible returns (Barberis & Huang, 2008), and (iii) the attractiveness of insurance (Wakker, Thaler, & Tversky, 1997). Similarly, insurance deductible choices reveal substantial overweighting of low probabilities and underweighting of high probabilities (Barseghyan, Molinari, O'Donoghue, & Teitelbaum, 2013).

***Step 2: Model Variables***

After selecting an appropriate predictive model, the challenge remains of correctly identifying key variables to which the model applies (i.e., the particular representation of acts, potential outcomes, and their corresponding probabilities for several models). In our review of prospect theory, we have already seen how framing, editing, and choice bracketing can affect decisions under risk through their effect on decision makers' cognitive representation of acts, outcomes, and probabilities. Researchers usually assume that most participants in laboratory studies accept the framing and bracketing of prospects as explicitly given. It is more challenging to determine how individuals abstract particular representations of decision problems in naturalistic settings.

To begin with, the representation of alternatives in naturalistic decision under risk may depend on a number of situational factors. As we discussed in Section 2.2, narrow bracketing of choices can support modest risk aversion for individual choices that manifests as extreme risk aversion in the aggregate. Perhaps the most obvious factor influencing bracketing is presentation timing. When decisions are presented concurrently, people tend to compare prospects and thus bracket broadly, whereas when decisions are made sequentially, people tend to consider decisions in isolation and thus bracket narrowly (Read, Loewenstein, & Rabin, 1999). For example, a CFO may adopt a broad bracket when making financial plans for a full year, but may bracket more narrowly when making day-to-day decisions.

Broad bracketing can be cognitively taxing, hence both individual differences in cognitive ability and momentary cognitive states may affect how broadly decision makers bracket their choices. As decision makers bracket more broadly, the number of potential interactions between choices can grow exponentially, thereby imposing sharply increasing cognitive demands; this may drive those with less cognitive capacity and/or less relevant experience to bracket more narrowly. Situational circumstances, such as conditions of resource scarcity, can cause individuals to focus their attention on the most pressing choices and therefore bracket decisions narrowly (Shah, Mullainathan, & Shafir, 2012). Evaluation systems may also influence choice bracketing; when decision makers feel accountable for the outcome of each individual decision they will tend to adopt narrower brackets (Swalm, 1966; Tetlock & Boettger, 1994), whereas when decision makers feel accountable for a portfolio of outcomes they will tend to bracket their choices more broadly.

After determining how decisions are bracketed, one must represent the possible outcomes of each alternative. In prospect theory, this requires identification of a typical decision maker's reference point so that one can determine the perceived valence of relevant outcomes to be modeled. As mentioned, the status quo typically serves as the reference point distinguishing losses from gains. However, reference points can also be determined by expectations (Kőszegi & Rabin, 2006) or prior outcomes (e.g., Baker, Pan, & Wurgler, 2012; Baucells, Weber, & Welfens, 2011). Furthermore, goals can serve as reference points, inducing people to take more risks when striving to achieve them, due to convexity of the value function below the reference point (Larrick, Heath, & Wu, 2009). In a dynamic context, decision makers may integrate or segregate various potential outcomes of a target prospect with past outcomes. For instance, decision makers tend to be more risk seeking following prior gains ("the house money effect") and when attempting to recoup a prior loss ("the break even effect"), and these phenomena can be accommodated by an application of prospect theory that incorporates "quasi-hedonic" editing rules governing the framing of outcomes (Thaler & Johnson, 1990).

Finally, when applying prospect theory to naturalistic environments we must consider how the probability distribution over possible outcomes is represented by the decision maker. In the field, this information is usually presented explicitly (e.g., as when a doctor presents to a patient the probability of side effects of a vaccine), represented endogenously (e.g., as when an investor considers the probability that a new technology will succeed), or learned through sampled experience (e.g., a driver learns the probability of getting into an accident when speeding by observing the results of this behavior over many driving episodes). While people tend to accurately encode the frequencies of discrete events they have observed in some simple experimental settings (Hasher & Zacks, 1984), they more generally tend to overestimate the relative frequency of rare events and underestimate the relative frequency of common events they have directly observed (e.g., Varey, Mellers, & Birnbaum, 1990), which will amplify the tendency to overweight low probability events and underweight high probability events that is observed in prospect theory. However, as previously mentioned, decisions from experience may lead to neglect of possible outcomes that have never been experienced because they may not be cognitively represented as possibilities (Hadar & Fox, 2009).

Risk taking in naturalistic settings appears to be critically influenced by individual differences in cognitive representation of probabilities and consequences. Studies have found that substantial variation in risk taking across life domains—for instance, financial versus recreational versus social risks—can largely be attributed to differences in perceived risks and/or benefits of such activities (Hanoch, Johnson, & Wilke, 2006; Weber, Blais, & Betz, 2002) rather than differences in risk preferences across domains. Naturally, a particular activity (e.g., hang gliding) may be perceived as “risky” to one person but not to another, and it may be seen as potentially rewarding to one person but not another.

### ***Step 3: Model Parameters***

The third step in constructing a predictive model of risk taking entails identifying relevant model parameters for the target population, group, or individual at the relevant moment in time. In some analyses it may be sufficient merely to consider qualitative aspects of a model (e.g., the value function is convex for losses and concave for gains; people are more sensitive to losses than gains) or plug in representative parameters from the populations (e.g., the coefficient of loss aversion, $\lambda$, is approximately 2.25; the exponent of the value function for gains, $\alpha$, is approximately 0.88; Tversky & Kahneman, 1992).

Of course, model parameters for typical individuals may vary with the particular decision situation. For instance, when people evaluate a stimulus with "affectively rich" consequences (e.g., a potential kiss or electrical shock versus money) they tend to exhibit a more pronounced four-fold pattern of risk preferences, suggesting a more inverse-S-shaped weighting function (Rottenstreich & Hsee, 2001). As discussed in Section 2.3, this effect might be driven by a more general tendency to be less sensitive to probabilities associated with non-monetary than monetary outcomes (McGraw, Shafir, & Todorov, 2010).

One can refine prediction of risk taking in the field if one measures individual differences in risk tolerance. Careful measurement of prospect theory parameters (e.g., Gonzalez & Wu, 1999) has yielded considerable between-participant variability. For instance, Gächter, Johnson, and Herrmann (2010) report a median loss aversion coefficient of 1.6 with a lower quartile of 1.2 and an upper quartile of 2.0. To put this in perspective, the mean difference between genders in the loss aversion coefficient was only 0.4. For a survey of measurement issues and parameters obtained in several studies, see Fox and Poldrack (2014). Unfortunately, researchers have thus far had only modest success using prospect theory to predict individual risk preference and risk taking in naturalistic settings. Prospect theory parameters exhibit relatively low test-retest reliability in that the measured parameters vary significantly over a one-month period for about one-sixth of the participants in the gain domain and for about one-third in the loss domain (Zeisberger, Vrecko, & Langer, 2011). Individual differences in carefully measured parameters have been found to be a relatively weak predictor of preferences among prospects modeled after real-world investments (Erner, Klos, & Langer, 2013), perhaps due to the complexity of those investments. Finally, we note that transitory cognitive states may influence measured prospect theory parameters. For instance, Stewart, Reimers, and Harris (2014) report that the measured parameters of prospect theory value and weighting functions can be systematically perturbed by altering the shape of the distribution of outcomes to which participants have recently been exposed, suggesting that individual-level preference parameters may fluctuate in response to recent experience.

Despite this lack of evidence that laboratory-measured individual differences in prospect theory parameters strongly predict naturalistic behaviors, there is ample evidence for consistent differences in risk taking between different demographic groups. Males exhibit greater risk tolerance than females both in the laboratory and field, with the gap being greatest among adolescents (Byrnes, Miller, & Schafer, 1999; Powell & Ansic, 1997). These gender differences may be driven partly by a tendency for women to perceive greater risk in many gambling, recreation, and health situations (Harris, Jenkins, & Glaser, 2006). In addition, women have been found to be less sensitive than men to differences in probability, and they also have been found to exhibit more underweighting of high probabilities than men (Fehr-Duda, de Gennaro, & Schubert, 2006). In some particular domains, such as social risk taking, women and men do not differ substantially (Harris, Jenkins, & Glaser, 2006). Cultural background may also influence risky choice. For instance, in one study Chinese students were more risk seeking than American students, though this phenomenon might be explained by decreased perceptions of risk among the Chinese due to enhanced "social cushioning" that exists in collectivist cultures in which one can feel more secure that family and friends will help provide financial support in the case of extreme losses (Weber & Hsee, 1998).

Perhaps even more compelling evidence for reliable individual differences in risk preference is the finding that genes responsible for differences in neurotransmitter activity predict risky choice behavior. In particular, variants of two genes (5-HTTLPR and DRD4) responsible for activity of the neurotransmitters dopamine and serotonin have been found to predict financial risk taking. The presence of these genes is linked to greater investment allocation to risky assets in a hypothetical investment task (Kuhnen & Chiao, 2009). Greater dopaminergic activity is associated with greater risk tolerance for gains (possibly reflecting more rapidly diminishing sensitivity over increasing gains), whereas lower serotonergic activity is associated with greater risk tolerance over losses (possibly reflecting more rapidly diminishing sensitivity to increasing losses; Zhong, Israel, Xue, Sham, Ebstein, & Chew, 2009).

Additional evidence for robust individual differences in risk preferences comes from the documented success of self-rating measures, such as the *sensation seeking* scale (Zuckerman, 2007), and clinical tasks, such as the *Balloon Analogue Risk Task (BART*; Lejuez, Read, Kahler, Richards, Ramsey, Stuart, Strong, & Brown, 2002) in predicting individual differences in various forms of naturalistic risk taking. Sensation seeking is a self-report measure of one's propensity to take risks in the pursuit of novel experiences, while the BART prompts participants to gradually pump up a computerized balloon with the goal of maximizing the number of pumps (each of which add a fixed amount of money to one's account) without overfilling and bursting the balloon (which wipes out all of the money accumulated on a given trial). Higher levels of sensation seeking have been linked to higher frequency of alcohol use (Andrew & Cronin, 1997) and more participation in high risk sports (Zarevski, Marušić, Zolotić, Bunjevac, & Vukosav, 1998), while greater tolerance among adolescents for pumping air into BART balloons has been linked to higher rates of gambling, drug use, and unprotected sex (Lejuez, Read, Kahler, Richards, Ramsey, Stuart, Strong, & Brown, 2002). Unfortunately, these measures are not decomposed readily into decision theoretic constructs, such as sensitivity to gains and losses, and do not distinguish individual differences in risk preferences from individual differences in risk perceptions (e.g., Schonberg, Fox, & Poldrack, 2011).

Proceeding a level deeper in our analysis, individual differences in sensitivity to outcomes and probability may fluctuate over time depending on a decision maker’s cognitive, emotional and/or motivational state. First, one’s current affective state may perturb value and weighting function parameters. For instance, when people are aroused, they are willing to pay less for insurance and more for lotteries (Mano, 1994). Second, people in a positive mood judge the utility of negative outcomes less favorably, suggesting a perturbation of the value function (Isen, Nygren, & Ashby, 1988). Moreover, people in a negative mood perceive negative events as more likely, regardless of the cause or the event’s relationship to their mood, suggesting a distortion of subjective probability estimates and/or probability weighting (Johnson & Tversky, 1983; Mayer, Gaschke, Braverman, & Evans, 1992). Also, women in a positive mood were found to weight probabilities more optimistically, while men did not show a significant effect of mood (Fehr-Duda, Epper, Bruhin, & Schubert, 2011). Third, specific affective states can induce different risk perceptions and preferences. For instance, chronic or induced fear appears to increase perception of riskiness and risk averse behavior, whereas chronic or induced anger has the opposite effect (Lerner, Gonzalez, Small, & Fischhoff, 2003; Lerner & Keltner, 2001).

There is some evidence that physiological states may be associated with fluctuations in risk preferences. Coates and Herbert (2008) measured professional traders’ levels of endogenous steroids in the morning and afternoon of a trading day. Higher levels of testosterone in the morning were significantly related to higher profits during the remainder of the trading day while levels of the stress hormone cortisol increased with greater variance of the trader’s profits and losses. In another study, when men viewed erotic photographs while stimulating themselves, they reported greater willingness to engage in risky or ethically questionable sexual behavior compared to when they were in a nonaroused state (Ariely & Loewenstein, 2006).

A number of additional state variables can distort risk preference parameters. For instance, people who are motivationally focused on *prevention* (as opposed to *promotion*) tend to take greater risks to maintain the status quo (Scholer, Zou, Fujita, Stroessner, & Higgins, 2010). Reminding people of their political identity increases the tendency of Republicans to choose financial risks labeled as "conservative" and modestly deters Democrats from doing so (Morris, Carranza, & Fox, 2008). Being touched by another person can induce feelings of security and greater propensity to take risks (Levav & Argo, 2010). Interestingly, after an episode of bad luck, hand washing appears to increase decision makers' subsequent tendency to take risks (Xu, Zwick, & Schwarz, 2012).

***Taking stock of differences between laboratory and field***

Having developed a conceptual framework for predicting naturalistic risk taking, we now return to the differences between laboratory and field settings that we articulated at the beginning of this section, and take stock of how each is addressed by the framework we have developed. First, as for complex contingencies outside the laboratory, we discussed how features of naturalistic settings, including complexity, enter into the construal of the decision situation and presumably affect which decision model is most predictively valid (step 1). More complex choices may, for instance, lead decision makers to rely on simplifying choice heuristics. Second, as for different domains of risk taking outside the laboratory, we discussed how naturalistic risk taking may differ in representation of model variables based on domain and context (step 2)—notably, such variation appears to be attributable to individual differences in risk perception across domains, as well as situational factors impacting the reference point of a typical decision maker. Third, as for emotion and meaning in risk taking outside the laboratory, we discussed how model parameters may be impacted by affective states and activated social identities. This can be captured partly by allowing model parameters to vary with affective, motivational, and cognitive states (step 3).

The final difference between laboratory and field, which we have not yet addressed, is the inherent presence of real incentives in the field. We note that several papers have examined differences in decision behavior when there are no incentives versus small or large financial incentives. The majority of these studies find that financial incentives increase risk aversion in the domain of gains (Battalio, Kagel, & Jiranyakul, 1990; Beattie & Loomes, 1997; Hogarth & Einhorn, 1990; Holt & Laury, 2002; Irwin, McClelland, & Schulze, 1992; Kachelmeier & Shehata, 1992; for a review see Camerer & Hogarth, 1999). However, Camerer (1989) found no difference in risk aversion with incentives while other experiments found greater risk seeking (Edwards, 1953; Grether & Plott, 1979). In some experiments where incentives did not change mean outcomes they did reduce response variance. For example, financial incentives administered using the popular Becker-DeGroot-Marschak (1964) procedure did not affect mean valuations of risky prospect, but reduced standard deviation by 50% (Irwin, McClelland, McKee, Schulze, & Norden, 1998). In contrast, in a study of risk preferences in the loss domain, people did not show significant differences between real losses, losses following an initial endowment provided by the experimenter, and hypothetical losses (though measured utility was slightly more concave for real losses; Etchart-Vincent & l'Haridon, 2012).

***Case Study***

To illustrate an application of our framework for modeling risk taking behavior outside the laboratory, suppose that George is deciding whether or not to purchase an extended warranty for a newly purchased wide screen television. We begin at the first step of our analysis (baseline model) by assuming that George, like most people, construes this kind of situation as a choice between a chance gamble and a sure payment, and therefore his decision making tendencies are well-characterized by prospect theory. Proceeding to the second step in our analysis (model variables), we might assume that George, like most people, adopts the status quo as the reference point and therefore represents his situation as a choice between losing the $2,000 he spent on his television with a probability of perhaps 10% (if the television breaks) or else paying $200 for an extended warranty to eliminate this possibility. The third step of this analysis (model parameters) entails determining relevant parameters to apply to the given instantiation of the selected model. Fitting representative prospect theory parameters to these variables, we might predict that George will be risk averse for a low probability loss, largely due to a common tendency to overweight a judged probability of 10%, and therefore he is likely to purchase the extended warranty.

Thus far, we have made a prediction based on typical behavior found in the general population. If we want to make a better prediction about George in particular, we can proceed to the next level of analysis by taking into account what we know about George’s individual differences (or differences that are characteristic of the groups to which George belongs). For instance, we may happen to know that George makes consumer warranty decisions using a simple heuristic that one should only buy insurance in cases where a substantial portion of his wealth is at risk—so that prospect theory is not the most descriptively valid model. However, if instead we assume as before that George thinks about such situations as chance gambles (so that prospect theory could be a valid model), proceeding to the second step (model variables) we may observe that George is a mathematician by training who tends to bracket extended warranty decisions broadly so that he will understand that the probability distribution over outcomes for a portfolio of extended warranty purchases is very unattractive compared to a portfolio in which he self-insures. However, supposing that we think that George brackets narrowly so that prospect theory applied to a single decision is appropriate, proceeding to the third step (model parameters) we may incorporate our knowledge that George is a male of Chinese ancestry and therefore we expect him to be more risk seeking than the average individual in the general population, due to base rates of these demographic groups. These assumptions might lead us to predict that he will self-insure and decline the warranty. Alternatively, we could have measured his individual prospect theory parameters to determine his typical risk preference when facing a low probability loss.

Thus far we have made a prediction based on our knowledge of George's individual and group-level differences. However, if we have more intimate knowledge of George's current cognitive, emotional, and/or motivational state, we may be able to refine our prediction further. For example, we may know that George is shopping under a great deal of time pressure so that he is more likely to decide about the warranty in a heuristic rather than integrative manner (step 1, baseline model) and therefore will be more susceptible than usual to the advice of a salesperson to buy the warranty. Or perhaps we know that George was nearly hit by a car on his way to the store, and is therefore in a somewhat fearful state at the moment of the decision, in which case we might predict an even greater tendency toward pessimistic beliefs (step 2, model variables) and risk aversion (step 3, model parameters) and is therefore more likely than usual to purchase the warranty.

## 5. Conclusion

In this chapter we have provided a broad behavioral perspective on decision under risk that has taken us from the field to the laboratory and back to the field. We began by stripping away complications that occur in naturalistic environments to motivate the decision theoretic perspective of modeling risky behavior by considering probability distributions over possible outcomes. We next traced the development of prospect theory, the leading behavioral model of decision under risk. We then noted several theoretical and empirical challenges to the general validity of prospect theory, and surveyed a number of alternative models that have been advanced in the literature. Finally, we attempted to bridge the gap between behavior in the laboratory and the field by articulating three steps of model building (baseline model, model variables, model parameters) and discussing three levels of analysis (typical behavior, individual differences, state differences).

Despite its limitations, we find that prospect theory is the most successful general-purpose model currently available for predicting, describing, and interpreting decisions under risk; to our reading alternative models that we reviewed outperform prospect theory only under specific conditions. Alternative models to prospect theory may be especially valuable in naturalistic conditions that mimic laboratory conditions under which those models fare especially well. We further observe that more successful predictions of decisions require a more nuanced analysis that incorporates an individual's construal of the decision situation, his or her individual sensitivity to probabilities and outcomes, and his or her current state of mind. Naturally, our simple analytical framework could be improved by operationalizing each level of analysis more precisely.

We suggest that there remain many interesting challenges for behavioral researchers who wish to improve prediction of risk taking in the field. First, further theory development is needed to understand how model selection (step 1 in our framework) is influenced by circumstances and individual differences. In this chapter we review four classes of empirically validated models, each with multiple sub-types. Each model has shown some promise at predicting risky decision making in different laboratory tests. However, the naturalistic factors driving a decision maker to behave in accordance with one model rather than another remain unknown in most cases and are only loosely defined in other cases.

Second, it may be useful to explore interactions between the levels (typical behavior, individual differences, state differences) of our framework. For example, the impact of state (level 3) on risk taking may be governed by individual differences (level 2), or individual differences in sophistication (level 2) may influence the complexity of a decision maker's analysis and therefore the choice of appropriate model (level 1). Researchers are already aware of some interactions, such as gender differences when measuring the impact of affective state on risk taking (Fehr-Duda, Epper, Bruhin, & Schubert, 2011). What cultural, genetic, or other individual differences might also moderate risk taking under various states? A deeper understanding of the relationship between the three steps and three levels will be needed to make more accurate predictions of risk taking in the field.

## References

Abdellaoui, M., Baillon, A., Placido, L., & Wakker, P. P. (2011). The rich domain of uncertainty: Source functions and their experimental implementation. *American Economic Review*, 101(2), 695-723.

Abdellaoui, M., l'Haridon, O., & Paraschiv, C. (2011). Experienced vs. described uncertainty: Do we need two prospect theory specifications? *Management Science*, 57(10), 1879-1895.

Allais, M. (1953). Le comportement de l'homme rationel devant le risque: Critique des postulates et axiomes de l'ecole americaine. *Econometrica*, 21(4), 503-546.

Andersen, S., Harrison, G. W., Lau, M. I., & Rutström, E. E. (2006). Elicitation using multiple price list formats. *Experimental Economics*, 9(4), 383-405.

Andrew, M. & Cronin, C. (1997). Two measures of sensation seeking as predictors of alcohol use among high school males. *Personality and Individual Differences*, 22(3), 393-401.

Ariely, D. & Loewenstein, G. (2006). The heat of the moment: The effect of sexual arousal on sexual decision making. *Journal of Behavioral Decision Making*, 19(2), 87-98.

Baker, M., Pan, X., & Wurgler, J. (2012). The effect of reference point prices on mergers and acquisitions. *Journal of Financial Economics*, 106(1), 49-71.

Barberà, S., Hammond, P., & Seidl, C. (eds.). (2004). *Handbook of Utility Theory: Volume 2 - Extensions*. Springer.

Barberis, N. C. (2013). Thirty years of prospect theory in economics: A review and assessment. *Journal of Economic Perspectives*, 27(1), 173-196.

Barberis, N. C. & Huang, M. (2008). Stocks as lotteries: The implications of probability weighting for security prices. *American Economic Review*, 98(5), 2066-2100.

Baron, J., & Spranca, M. (1997). Protected values. *Organizational Behavior and Human Decision Processes*, 70(1), 1-16.

Barseghyan, L., Molinari, F., O'Donoghue, T., & Teitelbaum, J. C. (2013). The nature of risk preferences: Evidence from insurance choices. *American Economic Review*, 103(6), 2499-2529.

Battalio, R. C., Kagel, J. H., & Jiranyakul, K. (1990). Testing between alternative models of choice under uncertainty: Some initial results. *Journal of Risk and Uncertainty*, 3(1), 25-50.

Baucells, M., Weber, M., & Welfens, F. (2011). Reference-point formation and updating. *Management Science*, 57(3), 506-519.

Beattie, J., & Loomes, G. (1997). The impact of incentives upon risky choice experiments. *Journal of Risk and Uncertainty*, 14(2), 155-168.

Becker, G. M., DeGroot, M. H., & Marschak, J. (1964). Measuring utility by a single-response sequential method. *Behavioral Science*, 9(3), 226-232.

Bell, D. E. (1982). Regret in decision making under uncertainty. *Operations Research*, 30(5), 961-981.

Bell, D. E. (1985). Disappointment in decision making under uncertainty. *Operations Research*, 33(1), 1-27.

Benartzi, S. & Thaler, R. H. (1995). Myopic loss aversion and the equity premium puzzle. *Quarterly Journal of Economics*, 110(1), 73-92.

Bernoulli, D. (1738). Specimen theoriae novae de mensura sortis. *Commentarii Academiae Scientiarum Imperialis Petropolitanae*, Tomus V, 175-192. Reprinted as: Bernoulli, D. (1954). Exposition of a new theory on the measurement of risk. *Econometrica*, 22(1), 23-36.

Birnbaum, M. H. (1974). The nonadditivity of personality impressions. *Journal of Experimental Psychology*, 102(3), 543-561.

Birnbaum, M. H. (1999). The paradoxes of Allais, stochastic dominance, and decision weights. In: J. Shanteau, B. A. Mellers, and D. A. Schum, D. A. (eds.), *Decision Science and Technology: Reflections on the Contributions of Ward Edwards* (pp. 27-52), Norwell, MA: Kluwer Academic Publishers.

Birnbaum, M. H. (2004). Causes of Allais common consequence paradoxes: An experimental dissection. *Journal of Mathematical Psychology*, 48(2), 87-106.

Birnbaum, M. H. (2005). Three new tests of independence that differentiate models of risky decision making. *Management Science*, 51(9), 1346-1358.

Birnbaum, M. H. (2008a). New paradoxes of risky decision making. *Psychological Review*, 115(2), 463-501.

Birnbaum, M. H. (2008b). Evaluation of the priority heuristic as a descriptive model of risky decision making: Comment on Brandstätter, Gigerenzer, and Hertwig (2006). *Psychological Review*, 115(1), 253-262.

Birnbaum, M. H. & Bahra, J. P. (2007). Gain-loss separability and coalescing in risky decision making. *Management Science*, 53(6), 1016-1028.

Birnbaum, M. H. & Chavez, A. (1997). Tests of theories of decision making: Violations of branch independence and distribution independence. *Organizational Behavior and Human Decision Processes*, 71(2), 161-194.

Birnbaum, M. H & Navarrete, J. B. (1998). Testing descriptive utility theories: Violations of stochastic dominance and cumulative independence. *Journal of Risk and Uncertainty*, 17(1), 49-78.

Bordalo, P., Gennaioli, N., & Shleifer, A. (2012). Salience theory of choice under risk. *Quarterly Journal of Economics*, 127(3), 1243-1285.

Brandstätter, E., Gigerenzer, G., & Hertwig, R. (2006). The priority heuristic: Making choices without trade-offs. *Psychological Review*, 113(2), 409-432.

Brandstätter, E. & Gussmack, M. (2013). The cognitive processes underlying risky choice. *Journal of Behavioral Decision Making*, 26(2), 185-197.

Bruhin, A., Fehr-Duda, H., & Epper, T. (2010). Risk and rationality: Uncovering heterogeneity in probability distortion. *Econometrica*, 78(4), 1375-1412.

Busemeyer, J. R. & Diederich, A. (2002). Survey of decision field theory. *Mathematical Social Sciences*, 43(3), 345-370.

Busemeyer, J. R. & Townsend, J. T. (1993). Decision field theory: A dynamic-cognitive approach to decision making in an uncertain environment. *Psychological Review*, 100(3), 432-459.

Byrnes, J. P., Miller, D. C., & Schafer, W. D. (1999). Gender differences in risk taking: A meta-analysis. *Psychological Bulletin*, 125(3), 367-383.

Camerer, C. F. (1989). An experimental test of several generalized utility theories. *Journal of Risk and Uncertainty*, 2(1), 61-104.

Camerer, C. F. (1995). Individual decision making. In: H. Kagel and A. E. Roth (eds.), *The Handbook of Experimental Economics* (pp. 587-703). Princeton University Press.

Camerer, C. F. & Ho, T. (1994). Violations of the betweenness axiom and nonlinearity in probabilities. *Journal of Risk and Uncertainty*, 8(2), 167-196.

Camerer, C. F. & Hogarth, R. M. (1999). The effects of financial incentives in experiments: A review and capital-labor-production framework. *Journal of Risk and Uncertainty*, 19(1-3), 7-42.

Chiu, A. & Wu, G. (2010). Prospect theory. In: J. J. Cochran (ed.), Wiley Encyclopedia of *Operations Research and Management Science*. Wiley.

Coates, J. M. & Herbert, J. (2008). Endogenous steroids and financial risk taking on a London trading floor. *Proceedings of the National Academy of Sciences*, 105(16), 6167-6172.

Cook, P. J. & Clotfelter, C. T. (1993). The peculiar scale economies of lotto. *American Economic Review*, 83(3), 634-643.

de Palma, A., Abdellaoui, M., Attanasi, G., Ben-Akiva, M., Fehr-Duda, H., Erev, I., Fok, D., Fox, C. R., Hertwig, R., Picard, N., Wakker, P. P., Walker, J. L., Weber, M. (2014). Beware of black swans and do not ignore white ones? Working Paper.

Edwards, W. (1953). Probability-preferences in gambling. *American Journal of Psychology*, 66(3), 349-364.

Ellsberg, D. (1961). Risk, ambiguity, and the savage axioms. *Quarterly Journal of Economics*, 75(4), 643-669.

Erner, C., Klos, A., & Langer, T. (2013). Can prospect theory be used to predict an investor's willingness to pay? *Journal of Banking and Finance*, 37(6), 1960-1973.

Etchart-Vincent, N. & l'Haridon, O. (2011). Monetary incentives in the loss domain and behavior toward risk: An experimental comparison of three reward schemes including real losses. *Journal of Risk and Uncertainty*, 42(1), 61-83.

Fehr-Duda, H., de Gennaro, M., & Schubert, R. (2006). Gender, financial risk, and probability weights. *Theory and Decision*, 60(2-3), 283-313.

Fehr-Duda, H., Epper, T., Bruhin, A., & Schubert, R. (2011). Risk and rationality: The effects of mood and decision rules on probability weighting. *Journal of Economic Behavior and Organization*, 78(1), 14-24.

Fiedler, S. & Glöckner, A. (2012). The dynamics of decision making in risky choice: An eye-tracking analysis. *Frontiers in Psychology*, 3(335), 1-18.

Figner, B. & Weber, E. U. (2011). Who takes risk when and why? Determinants of risk-taking. *Current Directions in Psychological Science*, 20(4), 211-216.

Finucane, M. L., Alhakami, A., Slovic, P., & Johnson, S. M. (2000). The affect heuristic in judgments of risks and benefits. *Journal of Behavioral Decision Making*, 13(1), 1-17.

Fischer, G. W., Carmon, Z., Ariely, D., & Zauberman, G. (1999). Goal-based construction of preferences: Task goals and the prominence effect. *Management Science*, 45(8), 1057-1075.

Fox, C. R. & Hadar, L. (2006). Decisions from experience = sampling error + prospect theory: Reconsidering Hertwig, Barron, Weber & Erev (2004). *Judgment and Decision Making*, 1(2), 159-161.

Fox, C. R., Long, A., Hadar, L., Erner, C. (2014). Unpacking the experience-description gap in decision under uncertainty. Working Paper, UCLA Anderson School of Management.

Fox, C. R. & Poldrack, R. A. (2014). Prospect theory and the brain. In P. Glimcher and E. Fehr (eds.), *Neuroeconomics: Decision Making and the Brain*, 2nd ed. (pp. 533-567). Amsterdam: Elsevier.

Fox, C. R., Rogers, B. A., & Tversky, A. (1996). Options traders exhibit subadditive decision weights. *Journal of Risk and Uncertainty*, 13(1), 5-17.

Fox, C. R. & See, K. E. (2003). Belief and preference in decision under uncertainty. In: D. Hardman and L. Macchi (eds.), *Thinking: Psychological Perspectives on Reasoning, Judgment and Decision Making* (pp. 273-314). Hoboken, NJ: Wiley.

Fox, C. R. & Tannenbaum, D. (2011). The elusive search for stable risk preferences. *Frontiers in Psychology*, 2, Article No. 298.

Fox, C. R. & Tversky, A. (1995). Ambiguity aversion and comparative ignorance. *Quarterly Journal of Economics*, 110(3), 585-603.

Fox, C. R. & Tversky, A. (1998). A belief-based account of decision under uncertainty. *Management Science*, 44(7), 879-895.

Fox, C. R. & Weber, M. (2002). Ambiguity aversion, comparative ignorance, and decision context. *Organizational Behavior and Human Decision Processes*, 88(1), 476-498.

Furby, L. & Beyth-Marom, R. (1992). Risk taking in adolescence: A decision-making perspective. *Developmental Review*, 12(1), 1-44.

Gächter, S., Johnson, E. J., & Herrmann, A. (2010). Individual-level loss aversion in riskless and risky choices. Working Paper, University of Nottingham.

Gigerenzer, G. & Gaissmaier, W. (2011). Heuristic decision making. *Annual Review of Psychology*, 62(1), 451-482.

Glöckner, A. & Betsch, T. (2008). Do people make decisions under risk based on ignorance? An empirical test of the priority heuristic against cumulative prospect theory. *Organizational Behavior and Human Decision Processes*, 107(1), 75-95.

Glöckner, A. & Herbold, A.-K. (2011). An eye-tracking study on information processing in risky decisions: Evidence for compensatory strategies based on automatic processes. *Journal of Behavioral Decision Making*, 24(1), 71-98.

Glöckner, A. & Pachur, T. (2012). Cognitive models of risky choice: Parameter stability and predictive accuracy of prospect theory. *Cognition*, 123(1), 21-32.

Gneezy, U., List, J. A., & Wu, G. (2006). The uncertainty effect: When a risky prospect is valued less than its worst outcome. *Quarterly Journal of Economics*, 121(4), 1283-1309.

Gneezy, U. & Potters, J. (1997). An experiment on risk taking and evaluation periods. *Quarterly Journal of Economics*, 112(2), 631-645.

Gonzalez, R. & Wu, G. (1999). On the shape of the probability weighting function. *Cognitive Psychology*, 38(1), 129-166.

Grether, D. M., & Plott, C. R. (1979). Economic theory of choice and the preference reversal phenomenon. *American Economic Review*, 69(4), 623-638.

Gul, F. (1991). A theory of disappointment aversion. *Econometrica*, 59(3), 667-686.

Hadar, L. & Fox, C. R. (2009). Information asymmetries in decisions from description versus decisions from experience. *Judgment and Decision Making*, 4(4), 317-325.

Hanoch, Y., Johnson, J. G., & Wilke, A. (2006). Domain specificity in experimental measures and participant recruitment: An application to risk-taking behavior. *Psychological Science*, 17(4), 300-304.

Harris, C. R., Jenkins, M., & Glaser, D. (2006). Gender differences in risk assessment: Why do women take fewer risks than men? *Judgment and Decision Making*, 1(1), 48-63.

Harrison, G. W. & Rutström, E. E. (2009). Expected utility theory and prospect theory: One wedding and a decent funeral. *Experimental Economics*, 12(2), 133-158.

Hasher, L., & Zacks, R. T. (1984). Automatic processing of fundamental information: the case of frequency of occurrence. *American Psychologist*, 39(12), 1372.

Heath, C., Larrick, R. P., & Wu, G. (1999). Goals as reference points. *Cognitive Psychology*, 38(1), 79-109.

Heath, C., & Tversky, A. (1991). Preference and belief: Ambiguity and competence in choice under uncertainty. *Journal of Risk and Uncertainty*, 4(1), 5-28.

Hershey, J. C., Kunreuther, H. C., & Schoemaker, P. J. (1982). Sources of bias in assessment procedures for utility functions. *Management Science*, 28(8), 936-954.

Hertwig, R., Barron, G., Weber, E. U., & Erev, I. (2004). Decisions from experience and the effect of rare events in risky choice. *Psychological Science*, 15(8), 534-539.

Hertwig, R. & Erev, I. (2009). The description-experience gap in risky choice. *Trends in Cognitive Sciences*, 13(12), 517-523.

Hilbig, B. E. (2008). One-reason decision making in risky choice? A closer look at the priority heuristic. *Judgment and Decision Making*, 3(6), 457-462.

Hogarth, R. M. & Einhorn, H. J. (1990). Venture theory: A model of decision weights. *Management Science*, 36(7), 780-803.

Holt, C. A. & Laury, S. K. (2002). Risk aversion and incentive effects. *American Economic Review*, 92(5), 1644-1655.

Huber J, Payne, J.W., & Puto, C. (1982). Adding asymmetrically dominated alternatives: Violations of regularity and the similarity hypothesis. *Journal of Consumer Research*, 9(1), 90-98.

Irwin, J. R., McClelland, G., McKee, M., Schulze, W. D., & Norden, N. E. (1998). Payoff dominance vs. cognitive transparency in decision making. *Economic Inquiry*, 36(2), 272-285.

Irwin, J. R., McClelland, G. H., & Schulze, W. D. (1992). Hypothetical and real consequences in experimental auctions for insurance against low-probability risks. *Journal of Behavioral Decision Making*, 5(2), 107-116.

Isen, A. M., Nygren, T. E., & Ashby, F. G. (1988). Influence of positive affect on the subjective utility of gains and losses: It is just not worth the risk. *Journal of Personality and Social Psychology*, 55(5), 710-717.

Jia, J., Dyer, J. S., & Butler, J. C. (1999). Measures of Perceived Risk. *Management Science*, 45(4), 519-532.

Johnson, E. J., Schulte-Mecklenbeck, M., & Willemsen, M. C. (2008). Process models deserve process data: Comment on Brandstätter, Gigerenzer, and Hertwig (2006). *Psychological Review*, 115(1), 263-273.

Johnson, E. & Tversky, A. (1983). Affect, generalization, and the perception of risk. *Journal of Personality and Social Psychology*, 45(1), 20-31.

Jullien, B., & Salanié, B. (2000). Estimating preferences under risk: The case of racetrack bettors. *Journal of Political Economy*, 108(3), 503-530.

Kachelmeier, S. J. & Shehata, M. (1992). Examining risk preferences under high monetary incentives: Experimental evidence from the People's Republic of China. *American Economic Review*, 82(5), 1120-1141.

Kahneman, D. & Lovallo, D. (1993). Timid choices and bold forecasts: A cognitive perspective on risk taking. *Management Science*, 39(1), 17-31.

Kahneman, D. & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica*, 47(2), 263-291.

Keren, G. & Willemsen, M. C. (2009). Decision anomalies, experimenter assumptions, and participants' comprehension: Revaluating the uncertainty effect. *Journal of Behavioral Decision Making*, 22(3), 301-317.

Knight, F. (1921). *Risk, Uncertainty, and Profit*. Boston, MA: Houghton-Mifflin.

Kőszegi, B. & Rabin, M. (2006). A model of reference-dependent preferences. *Quarterly Journal of Economics*, 121(4), 1133-1165.

Kuhnen, C. M. & Chiao, J. Y. (2009). Genetic determinants of financial risk taking. *PLoS One*, 4(2), e4362.

Kühberger, A. & Tanner, C. (2010). Risky choice framing: Task versions and a comparison of prospect theory and fuzzy-trace theory. *Journal of Behavioral Decision Making*, 23(3), 314-329.

Langer, E. J. (1975). The illusion of control. *Journal of Personality and Social Psychology*, 32(2), 311-328.

Larrick, R. P., Heath, C., & Wu, G. (2009). Goal-induced risk taking in negotiation and decision making. *Social Cognition*, 27(3), 342-364.

Lejuez, C. W., Read, J. P., Kahler, C. W., Richards, J. B., Ramsey, S. E., Stuart, G. L., Strong, D. R., & Brown, R. A. (2002). Evaluation of a behavioral measure of risk taking: the Balloon Analogue Risk Task (BART). *Journal of Experimental Psychology: Applied,* 8(2), 75-84.

Lerner, J. S. & Keltner, D. (2001). Fear, anger, and risk. *Journal of Personality and Social Psychology*, 81(1), 146-159.

Lerner, J. S., Gonzalez, R. M., Small, D. A., & Fischhoff, B. (2003). Effects of fear and anger on perceived risks of terrorism: A national field experiment. *Psychological Science*, 14(2), 144-150.

Levav, J. & Argo, J. J. (2010). Physical contact and financial risk taking. *Psychological Science*, 21(6), 804-810.

Loewenstein, G., Weber, E. U., & Hsee, C. K. (2001). Risk as feelings. *Psychological Bulletin,* 127(2), 267-286.

Loomes, G. & Sugden, R. (1982). Regret theory: An alternative theory of choice under uncertainty. *Economic Journal*, 92(368), 805-824.

Loomes G. & Sugden, R. (1986). Disappointment and dynamic consistency in choice under uncertainty. *Review of Economic Studies*, 53(2), 271-282.

Lopes, L. L. (1987). Between hope and fear: The psychology of risk. *Advances in Experimental Social Psychology*, 20(1), 255-295.

Lopes, L. L. & Oden, G. C. (1999). The role of aspiration level in risky choice: A comparison of cumulative prospect theory and SP/A theory. *Journal of Mathematical Psychology*, 43(2), 286-313.

Machina, M. J. (1987a). Choice under uncertainty: Problems solved and unsolved. *Economic Perspectives*, 1(1), 121-154.

Machina, M. J. (1987b). Decision-making in the presence of risk. *Science*, 236(4801), 537-543.

Mano, H. (1994). Risk-taking, framing effects, and affect. *Organizational Behavior and Human Decision Processes*, 57(1), 38-58.

March, J. G. & Shapira, Z. (1987). Managerial perspectives on risk and risk-taking. *Management Science*, 33(11), 1404-1418.

Markowitz, H. (1952). Portfolio selection. *Journal of Finance*, 7(1), 77-91.

Marley, A. A. J. & Luce, R. D. (2005). Independence properties vis-à-vis several utility representations. *Theory and Decision*, 58(1), 77-143.

Mayer, J. D., Gaschke, Y. N., Braverman, D. L., & Evans, T. W. (1992). Mood-congruent judgment is a general effect. *Journal of Personality and Social Psychology*, 63(1), 119-132.

McGraw, A. P., Shafir, E., & Todorov, A. (2010). Valuing money and things: Why a $20 item can be worth more and less than $20. *Management Science*, 56(5), 816-830.

Mellers, B. A, Schwartz, A., & Cooke, A. D. J. (1998). Judgment and decision making. *Annual Review of Psychology*, 49(-), 447-477.

Mellers, B. A., Schwartz, A., Ho, K., & Ritov, I. (1997). Decision affect theory: Emotional reactions to the outcomes of risky options. *Psychological Science*, 8(6), 423-429.

Morris, M. W., Carranza, E., & Fox, C. R. (2008). Mistaken identity activating conservative political identities induces “conservative” financial decisions. *Psychological Science*, 19(11), 1154-1160.

Newman, G. E. & Mochon, D. (2012). Why are lotteries valued less? Multiple tests of a direct risk-aversion mechanism. *Judgment and Decision Making*, 7(1), 19-24.

Odean, T. (1998). Are investors reluctant to realize their losses? *Journal of Finance*, 53(5), 1775-1798.

Payne, J. W. (2005). It is Whether You Win or Lose: The Importance of the Overall Probabilities of Winning or Losing in Risky Choice. *Journal of Risk and Uncertainty*, 30(1), 5-19.

Payne, J. W., Bettman, J. R., & Johnson, E. J. (1993). *The adaptive decision maker*. Cambridge University Press.

Pollatsek, A. & Tversky, A. (1970). A theory of risk. *Journal of Mathematical Psychology*, 7(3), 540-553.

Por, H.-H. & Budescu, D. V. (2013). Revisiting the gain-loss separability assumption in prospect theory. *Journal of Behavioral Decision Making*, 26(4), 385-396.

Powell, M. & Ansic, D. (1997). Gender differences in risk behaviour in financial decision-making: An experimental analysis. *Journal of Economic Psychology*, 18(6), 605-628.

Rabin, M. (2000). Risk aversion and expected utility theory: A calibration theorem. *Econometrica*, 68(5), 1281-1292.

Read, D., Loewenstein, G., & Rabin, M. (1999). Choice bracketing. *Journal of Risk and Uncertainty*, 19(1-3), 171-197.

Reyna, V. F. (2004). How people make decisions that involve risk: A dual process approach. *Current Directions in Psychological Science*, 13(2), 60-66.

Reyna, V. F. & Brainerd, C. J. (1995). Fuzzy-trace theory: An interim synthesis. *Learning and Individual Differences*, 7(1), 1-75.

Reyna, V. F. & Ellis, S. C. (1994). Fuzzy-trace theory and framing effects in children's risky decision making. *Psychological Science*, 5(5), 275-279.

Rieger, M. O. (2010). SP/A and CPT: A reconciliation of two behavioral decision theories. *Economics Letters*, 108(3), 327-329.

Rieger, M. O. & Wang, M. (2008). What is behind the priority heuristic? A mathematical analysis and comment on Brandstätter, Gigerenzer, and Hertwig (2006). *Psychological Review*, 115(1), 274-280.

Rothschild, M. & Stiglitz, J. E. (1970). Increasing risk: I. A definition. *Journal of Economic Theory*, 2(3), 225-243.

Rottenstreich, Y. & Hsee, C. K. (2001). Money, kisses, and electric shocks: On the affective psychology of risk. *Psychological Science*, 12(3), 185-190.

Rottenstreich, Y. & Kivetz, R. (2006). On decision making without likelihood judgment. *Organizational Behavior and Human Decision Processes*, 101(1), 74-88.

Rottenstreich, Y. & Shu, S. (2004). The connections between affect and decision making: Nine resulting phenomena. In: D. J. Koehler and N. Harvey (Eds.), *Blackwell Handbook of Judgment and Decision Making* (pp. 444-463). Hoboken, NJ: Wiley.

Rottenstreich, Y. & Tversky, A. (1997). Unpacking, repacking, and anchoring: Advances in support theory. *Psychological Review*, 104(2), 406–415.

Routledge, B. R., & Zin, S. E. (2010). Generalized disappointment aversion and asset prices. *The Journal of Finance*, 65(4), 1303-1332.

Rydval, O., Ortmann, A., Prokosheva, S., & Hertwig, R. (2009). How certain is the uncertainty effect? *Experimental Economics*, 12(4), 473-487.

Sarin, R. K. & Weber, M. (1993). Risk-value models. *European Journal of Operational Research*, 70(2), 135-149.

Schoemaker, P. J. H. (1982). The expected utility model: Its variants, purposes, evidence and limitations. *Journal of Economic Literature*, 20(2), 529-563.

Scholer, A. A., Zou, X., Fujita, K., Stroessner, S. J., & Higgins, E. T. (2010). When risk seeking becomes a motivational necessity. *Journal of Personality and Social Psychology*, 99(2), 215-231.

Schonberg, T., Fox, C. R., & Poldrack, R. A. (2011). Mind the gap: Bridging economic and naturalistic risk-taking with cognitive neuroscience. *Trends in Cognitive Sciences*, 15(1), 11-19.

Schulte-Mecklenbeck, M., Kühberger, A., & Ranyard, R. (2011). The role of process data in the development and testing of process models of judgment and decision making. *Judgment and Decision Making*, 6(8), 733-739.

Shafir E, Simonson I, & Tversky A. (1993). Reason-based choice. *Cognition*, 49(1-2), 11-36.

Shah, A. K., Mullainathan, S., & Shafir, E. (2012). Some Consequences of Having Too Little. *Science*, 338(6107), 682-685.

Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. *Journal of Finance*, 19(3), 425-442.

Shefrin, H. & Statman, M. (1985). The disposition to sell winners too early and ride losers too long: Theory and evidence. *Journal of Finance*, 40(3), 777-790.

Shefrin, H. & Statman, M. (2000). Behavioral portfolio theory. *Journal of Financial and Quantitative Analysis*, 35(2), 127-151.

Simonsohn, U. (2009). Direct risk aversion: Evidence from risky prospects valued below their worst outcome. *Psychological Science*, 20(6), 686-692.

Slovic, P. (1987). Perception of risk. *Science*, 236(4799), 280-285.

Slovic, P., Finucane, M. L., Peters, E., & MacGregor, D. G. (2007). The affect heuristic. *European Journal of Operational Research*, 177(3), 1333-1352.

Snowberg, E. & Wolfers, J. (2010). Explaining the favorite-long shot bias: Is it risk-love or misperceptions? *Journal of Political Economy*, 118(4), 723-746.

Starmer, C. (2000). Developments in non-expected utility theory: The hunt for a descriptive theory of choice under risk. *Journal of Economic Literature*, 38(2), 332-382.

Starmer, C. & Sugden, R. (1993). Testing for juxtaposition and event-splitting effects, *Journal of Risk and Uncertainty*, 6(3), 235-254.

Steinberg, L. (2008). A social neuroscience perspective on adolescent risk-taking. *Developmental Review*, 28(1), 78-106.

Stewart, N., Reimers, S., & Harris, A. J. (2014). On the origin of utility, weighting, and discounting functions: How they get their shapes and how to change their shapes. *Management Science*, published online before print, doi: 10.1287/mnsc.2013.1853.

Swalm, R. O. (1966). Utility theory-insights into risk taking. *Harvard Business Review*, 44(6), 123-136.

Taleb, N. N. (2007). *The Black Swan: The Impact of the Highly Improbable*. New York, NY: Random House.

Tetlock, P. E. & Boettger, R. (1994). Accountability amplifies the status quo effect when change creates victims. *Journal of Behavioral Decision Making*, 7(1), 1-23.

Thaler, R. H. & Johnson, E. J. (1990). Gambling with the house money and trying to break even: The effects of prior outcomes on risky choice. *Management Science*, 36(6), 643-660.

Thaler, R. H. & Ziemba, W. T. (1988). Anomalies: Parimutuel betting markets: Racetracks and lotteries. *Journal of Economic Perspectives*, 2(2), 161-174.

Trepel, C., Fox, C. R., & Poldrack, R. A. (2005). Prospect theory on the brain? Toward a cognitive neuroscience of decision under risk. *Cognitive Brain Research*, 23(1), 34-50.

Tversky, A. (1996). Contrasting rational and psychological principals of choice. In: R. J. Zeckhauser, R. L. Keeney, and J. K. Sebenius (eds.), *Wise Choices: Decisions, Games, and Negotiations* (pp. 5-21). Boston, MA: Harvard Business School Press.

Tversky, A. & Fox, C. R. (1995). Weighing risk and uncertainty. *Psychological Review*, 102(2), 269-283.

Tversky, A. & Kahneman, D. (1981). The framing of decisions and the psychology of choice. *Science*, 211(4481), 453-458.

Tversky, A. & Kahneman, D. (1986). Rational choice and the framing of decisions. *Journal of Business*, 59(4), Part 2, S251-S278.

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

Tversky, A. & Koehler, D. J. (1994). Support theory: A nonextensional representation of subjective probability. *Psychological Review*, 101(4), 547-567.

Tversky, A., Slovic, P., & Kahneman, D. (1990). The causes of preference reversal. *American Economic Review*, 80(1), 204-217.

Tversky, A. & Wakker, P. P. (1995). Risk attitudes and decision weights. *Econometrica*, 63(6), 1255-1280.

Ungemach, C., Chater, N., & Stewart, N. (2009). Are probabilities overweighted or underweighted, when rare outcomes are experienced (rarely)? *Psychological Science*, 20(4), 473-479.

Varey, C. A., Mellers, B. A., & Birnbaum, M. H. (1990). Judgments of proportions. *Journal of Experimental Psychology: Human Perception and Performance*, 16(3), 613-625.

Viscusi, W. K., Magat, W. A., & Huber, J. (1987). An investigation of the rationality of consumer valuations of multiple health risks. *RAND Journal of Economics*, 18(4), 465-479.

von Neumann, J. & Morgenstern, O. (1947). *Theory of Games and Economic Behavior*, 2nd ed. Princeton, NJ: Princeton University Press.

Wakker, P. P. (2001). Testing and characterizing properties of nonadditive measures through violations of the sure-thing principle. *Econometrica*, 69(4), 1039-1059.

Wakker, P. P. (2004). On the composition of risk preference and belief. *Psychological Review*, 111(1), 236-241.

Wakker, P. P. (2010). *Prospect Theory for Risk and Ambiguity*. Cambridge: Cambridge University Press.

Wakker, P. P., Thaler, R. H., & Tversky, A. (1997). Probabilistic Insurance. *Journal of Risk and Uncertainty*, 15(1), 7-28.

Weber, E. U., Ames, D. R., & Blais, A. R. (2005). 'How Do I Choose Thee? Let me Count the Ways': A Textual Analysis of Similarities and Differences in Modes of Decision-making in China and the United States. *Management and Organization Review*, 1(1), 87-118.

Weber, E. U., Blais, A.-R., & Betz, N. (2002). A domain-specific risk-attitude scale: Measuring risk perceptions and risk behaviors. *Journal of Behavioral Decision Making*, 15(4), 263-290.

Weber, E. U. & Hsee, C. (1998). Cross-cultural differences in risk perception, but cross-cultural similarities in attitudes towards perceived risk. *Management Science*, 44(9), 1205-1217.

Weber, E. U. & Milliman, R. A. (1997). Perceived risk attitudes: Relating risk perception to risky choice. *Management Science*, 43(2), 123-144.

Wedell, D. H. (1991). Distinguishing among models of contextually induced preference reversals. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 17(4), 767-778.

Whitney, P., Rinehart, C. A., & Hinson, J. M. (2008). Framing effects under cognitive load: The role of working memory in risky decisions. *Psychonomic Bulletin and Review*, 15(6), 1179-1184.

Wu, G. & Gonzalez, R. (1996). Curvature of the probability weighting function. *Management Science*, 42(12), 1676-1690.

Wu, G. & Gonzalez, R. (1998). Common consequence effects in decision making under risk. *Journal of Risk and Uncertainty*, 16(1), 115-139.

Wu, G. & Markle, A. B. (2008). An empirical test of gain-loss separability in prospect theory. *Management Science*, 54(7), 1322-1335.

Wu, G., Zhang, J., & Gonzalez, R. (2004). Decision under risk. In: D. J. Koehler and N. Harvey (eds.), *Blackwell Handbook of Judgment and Decision Making* (pp. 399-423). Hoboken, NJ: Wiley.

Xu, A. J., Zwick, R., & Schwarz, N. (2012). Washing away your (good or bad) luck: Physical cleansing affects risk-taking behavior. *Journal of Experimental Psychology: General*, 141(1), 26-30.

Yang, Y., Vosgerau, J., & Loewenstein, G. (2013). Framing influences willingness to pay but not willingness to accept. *Journal of Marketing Research*, 50(6), 725-738.

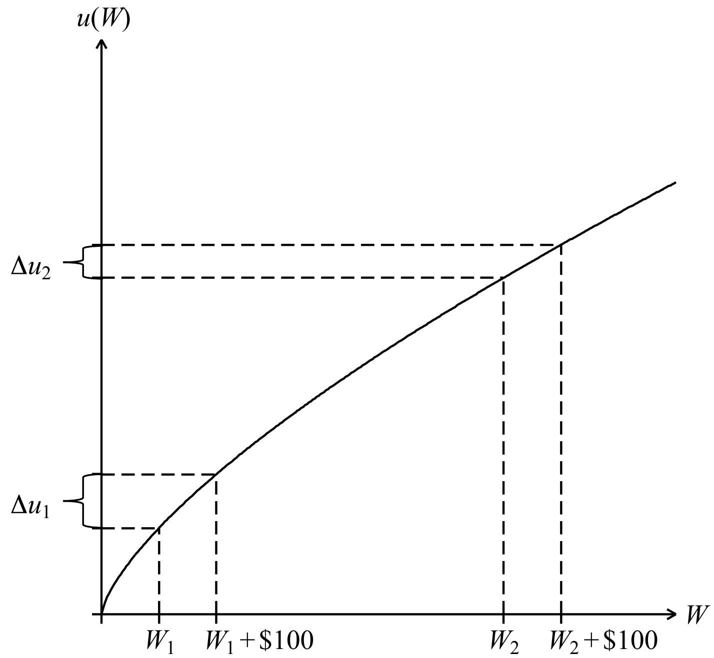
Zarevski, P., Marušić, I., Zolotić, S., Bunjevac, T., & Vukosav, Ž. (1998). Contribution of Arnett's inventory of sensation seeking and Zuckerman's sensation seeking scale to the differentiation of athletes engaged in high and low risk sports. *Personality and Individual Differences*, 25(4), 763-768.

Zeisberger, S., Vrecko, D., & Langer, T. (2011). Measuring the time stability of prospect theory preferences. *Theory and Decision*, 72(3), 359-386.

Zhong, S., Israel, S., Xue, H., Sham, P. C., Ebstein, R. P., & Chew, S. H. (2009). A neurochemical approach to valuation sensitivity over gains and losses. *Proceedings of the Royal Society B: Biological Sciences*, 276(1676), 4181-4188.

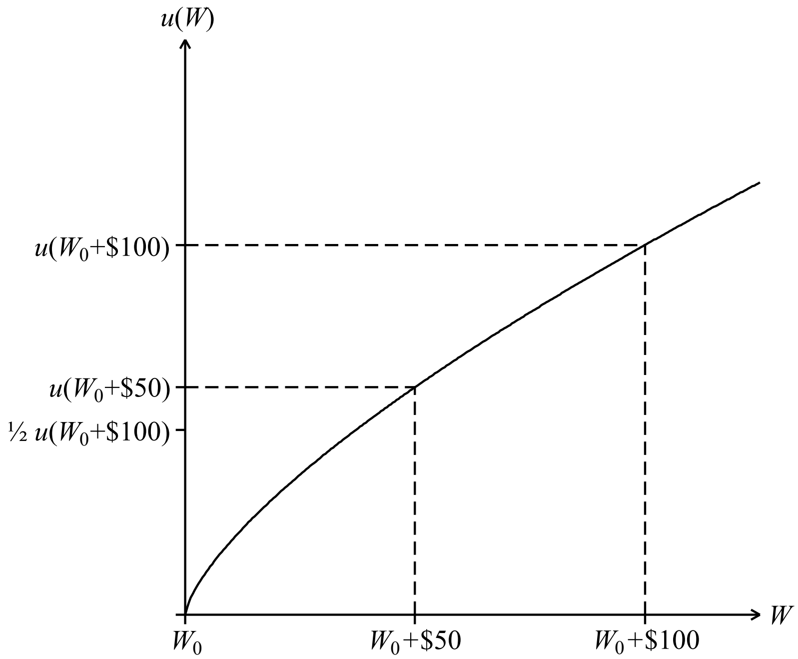
Zuckerman, M. (2007). The sensation seeking scale V (SSS-V): Still reliable and valid. *Personality and Individual Differences*, 43(5), 1303-1305.

**Figure 1: Diminishing Marginal Utility**



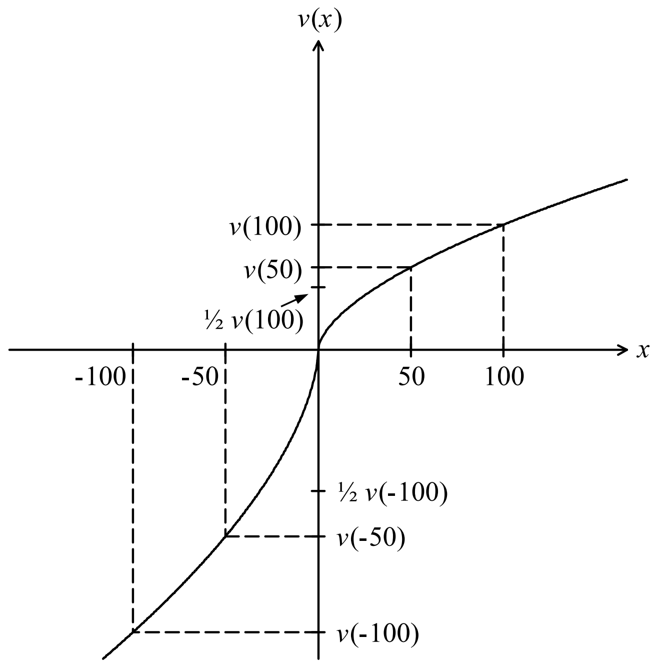

A concave utility function over states of wealth that is characterized by diminishing marginal utility.

**Figure 2: A Concave Utility Function Implies Risk Aversion**



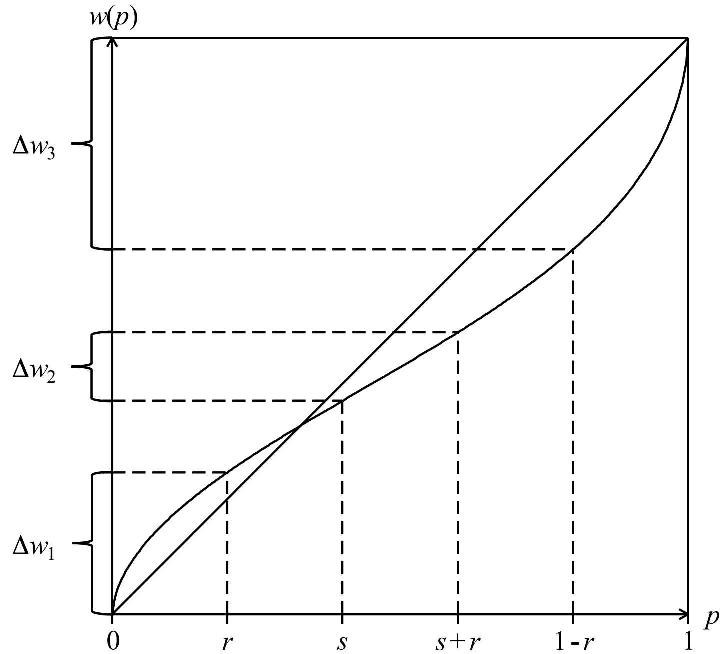

A visual depiction of how a concave utility function predicts risk aversion in the case of the choice of {gain \$50 for sure} over {a 50% chance to gain \$100 or else gain nothing}.

**Figure 3: Value Function of Prospect Theory**



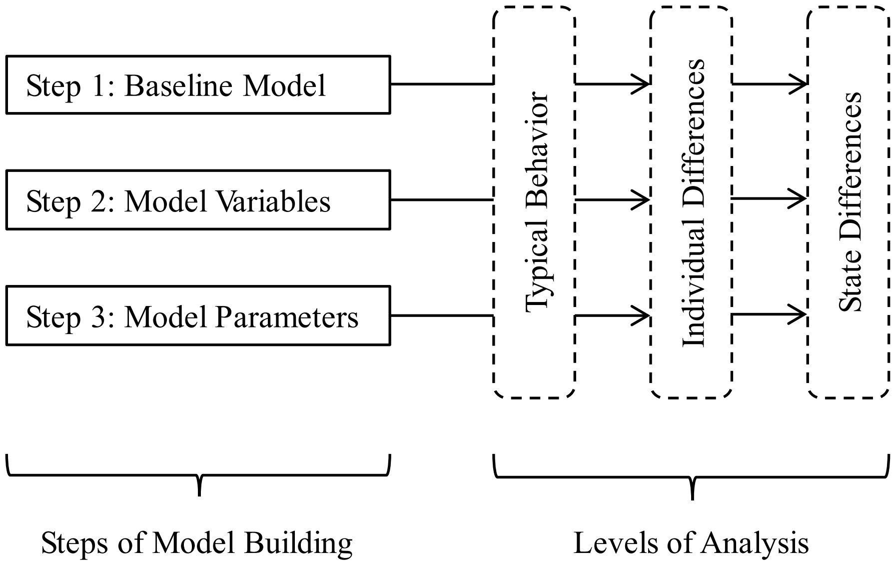

A representative value function from prospect theory depicting the subjective value of money gained or lost relative to a reference point.

**Figure 4: Probability Weighting Function of Prospect Theory**




A representative probability weighting function from prospect theory depicting the impact of various probabilities on the valuation of a prospect.

**Figure 5: Framework**




Framework for building a model of behavior, consisting of three steps of model building (baseline model, model variables, model parameters) and three levels of analysis (typical behavior, individual differences, state differences).

**Table 1: Fourfold Pattern of Risk Attitudes**

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

The fourfold pattern of risk attitudes (adapted from Tversky & Kahneman, 1992). CE($x$,$p$) is the certainty equivalent of the prospect that pays \$$x$ with probability $p$.

**Table 2: 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 |

Risk aversion for mixed (gain-loss) gambles (adapted from Tversky & Kahneman, 1992). The first column lists the median amount of money such that participants found a prospect that offered a 50% chance of gaining that amount or else losing the corresponding amount in the second column equally attractive to the prospect of receiving nothing.