2 Theories of Economic Decision-Making: Value, Risk and Affect

ANTON KÜHBERGER AND MICHAEL SCHULTE-MECKLENBECK

CHAPTER OUTLINE

LEARNING OUTCOMES

BY THE END OF THIS CHAPTER YOU SHOULD BE ABLE TO:

1. Identify and explain the major models of combining value and uncertainty.
2. Calculate the utility of a prospect according to SEU, and according to prospect theory.
3. Explain how affect and emotion can interact with cognitions in risky decision situations.

Economic Psychology
Edited by Rob Ranyard
© 2018 John Wiley & Sons Ltd

2.1 INTRODUCTION

Economic decision-making deals with various aspects of people's economic choices. In this process, the value of options is evaluated; but often options are not available for certain, and in such situations, risk becomes important. People may feel happy or sad about a situation or the outcomes of a choice, thus affect plays an important role. Understanding how value, risk and affect interact to form a coherent group of behaviours called risky decision-making is the main aim of this chapter. In what follows, we will give an overview of relevant concepts, such as value and utility, risk and ambiguity, affect and emotion, review the empirical research that informs the development of theory, and discuss relevant developments and interactions.

2.2 VALUE AND UTILITY

Theories of decision-making have their roots in economics (see Caplin & Glimcher, 2014), when researchers began to ask how the prices of traded goods come about. A striking first idea was that the price of a good produced by human effort depends on the number of labour hours it takes to produce it (the labour theory of value). It soon became clear that value accrues not only from labour. The so-called *marginal revolution* solved this problem. The new idea was to construe price as the marginal value of a good instead of its average value. Crucially, the marginal value of some good decreases as its total amount increases. Thus, for instance, stones are cheaper than diamonds because they are plentiful in most circumstances. If they were to become rare, their price would increase. An immediate question followed: why would someone be willing to pay so much more for exactly the same good if it was rare rather than plentiful? A person derives more happiness from the first item of a good compared to the, say, fifth item in her possession. Pricing thus follows from the decision-makers' goal to maximize happiness and/or satisfaction. Using the magical word: people are *utility*-maximizers.

The concept of utility became one of the backbones of the theory of economic decision-making. The historical record identifies a central paper on utility written by Nicolaus Bernoulli and published by his brother Daniel in the *St. Petersburg Academy Proceedings*. Bernoulli (1954 [1738]) proposed a solution for the so-called St. Petersburg Paradox (Box 2.1).

To solve the paradox, Bernoulli suggested distinguishing the utility – the desirability or satisfaction – of an outcome from its monetary amount (i.e., its value), and assuming a *principle of decreasing marginal utility*. This principle states that marginal utility (i.e., the utility obtained from an increment of some good) decreases as the quantity consumed increases. In other words, each additional amount of a good consumed is less satisfying than the previous one. Bernoulli additionally suggested a reasonable functional form for utility: the logarithm of the amount. By doing this the sum of expected utilities reaches a limit and the St. Petersburg game is worth the equivalent of about £4.00. The rational gambler, then, would pay any sum less than £4.00 to play. Thus, Bernoulli presented an ingenious solution of the paradox, and decreasing marginal utility became a new yardstick for reason and rationality.

Box 2.1 The St Petersburg Paradox

Consider the following gamble: you flip a fair coin until it comes up tails. The total number of flips, n, determines the prize you get, which equals £2^n. Thus, if the coin comes up tails the first time, the prize is £2^1 = £2, and the game ends. If the coin comes up heads, you flip it again. If it comes up tails the second time, the prize is £2^2 = £4, and the game ends. If it again comes up heads, it is flipped again. And so on. What is the value of this gamble? It is the sum of the payoffs of all the possible outcomes. In the first toss, the probability of tails is ½, and the payoff is £2. There are further possible outcomes, however: heads first, then tails. The probability of this sequence is ¼, and the payoff is £4. On we go, as long as further possibilities exist: heads, heads, tails. The probability of this sequence is ⅛, and the payoff is £8. We see that the probability of longer sequences of heads decreases, but never reaches zero. Calculation of the to-be-expected value (EV) shows:

$$\begin{aligned} EV &= \tfrac{1}{2} \times 2 + \tfrac{1}{4} \times 4 + \tfrac{1}{8} \times 8 + \ldots \\ &= 1 + 1 + 1 + 1 + \ldots \text{ ad infinitum} \end{aligned}$$

EV is an infinite large sum. Thus, a rational gambler should be willing to bet his or her entire fortune to play this gamble. Alas, paradoxically, 'few of us would pay even $25 to enter such a game' (Hacking, 1983, p. 563).

Researchers began to treat utility as something real, and tried to measure it. Consider this example, however. Imagine Tom prefers apples over oranges, oranges over bananas, and apples over bananas (i.e., apples ≻ oranges ≻ bananas). To explain Tom's preferences, we assign a 'fruit' utility to him of 3 for apples, 2 for oranges, and 1 for bananas. Unfortunately, we could also double, or halve the utilities, to predict the same preferences. The assigned utilities are useful for ordering things, but they fail on one simple test of rationality. This test has become famous as the *money pump* (Davidson, McKinsey, & Suppes, 1955). Box 2.2 gives an example of the logic behind it.

Box 2.2 The money pump

Imagine you prefer apples over oranges or you are indifferent; you prefer oranges over bananas or you are indifferent; you prefer bananas over apples or you are indifferent. Formally:

$$\text{apples} \succsim \text{oranges; oranges} \succsim \text{bananas;} \quad \text{bananas} \succsim \text{apples}$$

You have a banana. Now you are offered an orange for your banana plus 1¢. You accept – recall that you like oranges more than bananas. Then you are offered an apple for the orange plus 1¢. Again, you accept (apples are better than oranges). Finally, you are offered to sell back your original banana for the apple plus 1¢. Again, you accept (as you prefer bananas over apples). Based on your preferences you consider each trade a good one, however, looking at the final state, you own your original banana and you have lost 3¢. Obviously, this is not a good deal: because of your inconsistent preferences, it turns you into a money pump in repeated choices.

2.3 RISK AND UNCERTAINTY

We face uncertainties in many situations throughout our lives. Tannert, Elvers, and Jandrig (2007) proposed a taxonomy of uncertainty that pits the mismatch between the knowledge required and the knowledge available for rational decision-making. Their basic distinction is between *objective* and *subjective uncertainty*. Kahneman and Tversky (1982) proposed a similar distinction between *externally* attributed uncertainty and *internally* attributed uncertainty. External uncertainty is based on frequencies or on propensities; internal uncertainty can be based on arguments or on knowledge. Kahneman and Tversky showed that people use different ways to resolve these different forms of uncertainty.

In addition, it is useful to distinguish two further variants of uncertainty based on frequencies: whether the distribution of possible outcomes is known, or is not known (Knight, 1921). In decisions under risk, the outcomes and the associated uncertainties are known. Most experimental work on human choice has focused on decisions under risk (Weber, Shafir, & Blais, 2004). However, many real-world decisions come with uncertainty, rather than risk, because the distribution of outcomes is unknown. For example, accepting one job over another entails many uncertainties about the possible states of the world if one had decided differently.

2.3.1 From Expected Value to (Subjective) Expected Utility

How can we combine uncertainty and value? Early considerations resolved around a quite mundane problem: how to bet wisely in a lottery. Blaise Pascal recognized that choosing wisely involves picking the option that provides the best combination of value (v) and probability (p). He proposed calculating $v \times p$, i.e., the *expected value* (*EV*), and to evaluate lotteries according to this property. Mathematical expectation, and its maximization (i.e., choosing the option with the highest EV), became the central doctrine of how to choose in a rational manner.

Yet, there are problems with this approach. First, lotteries are a simplified model of the uncertainties faced in the world. It is questionable whether they provide an adequate description of real-life decisions (see Box 2.1, the St Petersburg Paradox), Indeed, people often fail to maximize EV, making EV a poor predictor of choice.

Second, how can the doctrine of EV be applied to uncertain (i.e., ambiguous) situations? The best-known solution is to turn uncertainty into risk by replacing objective probabilities by subjective ones (Savage, 1954). Objective probabilities are determined by physical facts, whereas subjective probability (or perceived risk) is the personal or social construction of belief that can be independent of physical facts. This conception of risk led to a new model – the *subjective expected utility* model (SEU).

Imagine a choice between two insurance policies. One covers your damage with 90% probability, and the other does the same with 45% probability. Is the first policy exactly twice as good as the second?

To answer such questions, von Neumann and Morgenstern (1944) formulated a set of axioms that need to be fulfilled when measuring subjective expected utility (see Box 2.3). They stated the transitivity axiom as a basis for ordering lotteries. They then took care that there were no abrupt jumps in preference following from small

Box 2.3 Important axioms of SEU, technically stated, and examples

Axiom of completeness: Either a $\succsim$ b, or b $\succsim$ a, or a $\sim$ b.

Example (colour preference): Either you prefer azure over blue, or blue over azure, or you are indifferent between azure and blue.

Axiom of transitivity: If a $\succsim$ b and b $\succsim$ c, then a $\succsim$ c.

Example: If you prefer azure over blue, and blue over cyan, you also prefer azure over cyan.

Axiom of continuity: b $\sim$ pa + (1-p)c.

Example: If it is true that azure $\succsim$ blue $\succsim$ cyan, then you are indifferent between blue and (azure with probability p and cyan with probability 1-p).

Axiom of independence: If a $\succsim$ b, then xa + (1-x)c $\succsim$ xb + (1-x)c.

Example: If you prefer azure over blue, and blue over cyan, you also prefer (50% azure and 50% blue) to (50% azure and 50% cyan).

differences in value or probability, by introducing the continuity axiom. Finally, they introduced the independence axiom, which ensures that adding or subtracting a common prize to a pair of lotteries does not change preference.

Armed with these axioms, it is possible to measure utility by having people decide between lotteries. However, researchers discovered that many decisions do not conform to this set of axioms. Investigating the scope of violations of the axioms has been one of the major issues of behavioural decision theory in the last 50 years. Among the classic demonstrations of failure of some axioms are: the *Allais paradox* (Allais, 1953; also called the *certainty effect*, Kahneman & Tversky, 1979); risk aversion for losses (*loss aversion;* Kahneman & Tversky, 1979); *ambiguity aversion* as demonstrated in the *Ellsberg effect* (Ellsberg, 1961); failure of descriptive invariance of identical situations (the *framing effect;* Tversky & Kahneman, 1981). To account for these violations, SEU was adapted and extended.

2.4 DEVELOPMENTS BASED ON SUBJECTIVELY EXPECTED UTILITY (SEU)

Imagine playing the popular television game show *Deal or No Deal*. As the show approaches the end, two possible prizes are left: the largest prize (£100,000) and the smallest one (£1). One of those prizes is in a box next to you. The gameshow host offers you £20,000 for that box: you thus have to choose between £20,000 for sure (EV: $20{,}000 \times 1 = 20{,}000$), or a 50% chance of £100,000 and a 50% chance of £1 (EV: $100{,}000 \times .50 + 1 \times .50 = 50{,}000.5$). What do you choose? Wouldn't it be tempting to take the £20,000, even though that has a much lower expected value?

This example shows a clash between the clever thing and the rational thing to do. Many of those clashes are addressed by another, if not the, prominent theory of risk and uncertainty, which we will discuss next.

2.4.1 Prospect Theory

The most successful development of SEU was prospect theory (PT), proposed by Kahneman and Tversky (1979); this was further developed as cumulative prospect theory by Tversky and Kahneman (1992). PT entails separate functions for the evaluation of probabilities, and for the translation of objective value into subjective utility.

The theory distinguishes two phases of decision-making: the editing phase, in which outcomes are assigned a subjective value by coding them in relation to some reference point, and probabilities are translated into decision weights. In the subsequent evaluation phase, the prospect with the highest evaluation is chosen. One of PT's essential new ideas relates to the editing phase and its value function. This function is defined over gains and losses relative to some reference point, shows diminishing sensitivity in both gains and losses, and is steeper for losses than for gains.

These properties of valuation have important consequences. Diminishing sensitivity is a general feature of evaluative processes, reflecting the basic psychophysical principle that the difference between £1 and £2 seems bigger than the difference between £101 and £102. Above the reference point, the value function is concave, below the reference point, it is convex. The shape of the value function is also steeper when losses are involved. This reflects loss aversion: for identical amounts, the reaction to losses is stronger than the reaction to gains.

PT's weighting function applies diminishing sensitivity to probabilities: There are two salient reference points for the evaluation of probabilities, namely, certainty ($p = 1$), and impossibility ($p = 0$). As people move away from these reference points, they become less sensitive to changes. They thus show a stylized pattern: they overweigh very small and underweigh very large probabilities. This gives rise to a weighting function that is concave near impossibility and convex near certainty (see Figure 2.1).

PT is formulated as:

$$V(x, p; y, q) = \pi(\mathrm{p})v(x) + \pi(\mathrm{q})v(y).$$

V denotes the value function for an option with two possible outcomes, x with probability p, and y with probability q; $v(0) = 0$, and π denoting the weighting function

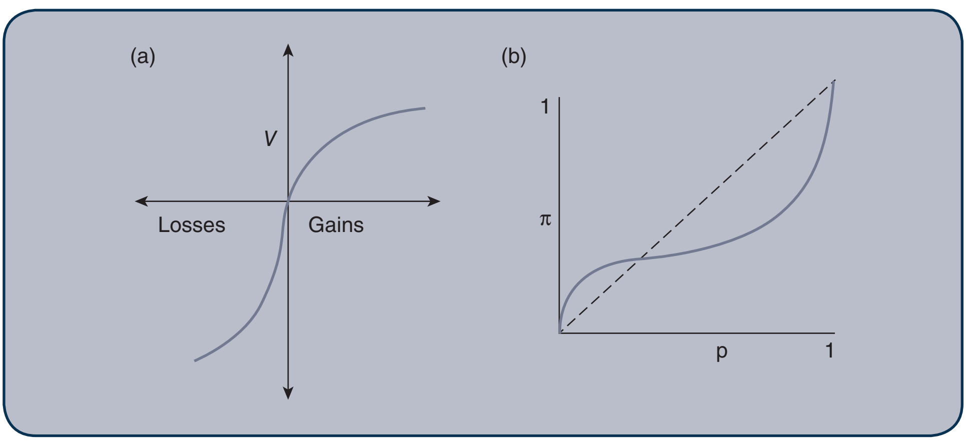

FIGURE 2.1 *Schematic form of (a) value-function and (b) weighting-function in prospect theory.*

Source: Adapted from Dreher 2007 with permission of Elsevier.

with $\pi(O) = 0$, and $\pi(1) = 1$ (Kahneman & Tversky, 1979, p. 276). PT descriptively explains a large number of so-called biases in risky decisions, such as loss aversion (Kahneman, Knetsch, & Thaler, 1991), the framing effect (Tversky & Kahneman, 1981), the endowment effect (Knetsch & Sinden, 1984; but see Kogler, Kühberger, & Gilhofer, 2013), the status quo bias (Samuelson & Zeckhauser, 1988), or the fourfold pattern of risk attitude (cumulative prospect theory: Tversky & Kahneman, 1992). This work was honoured in 2002 by the award of the Nobel Prize in Economics to Daniel Kahneman.

2.5 BEYOND UTILITY-BASED THEORIES

2.5.1 Process Models of Risky Choice

Until now we have only looked at the final choice as the central dependent measure. This allows for the construction of input-output models of risky choice. However, many researchers asked for tools and analyses also covering the information acquisition process, before a choice takes place (for an overview, see Schulte-Mecklenbeck, Kühberger, & Ranyard, 2011). Many of the more recent process-tracing tools are freely available, such as MouselabWeb (http://www.mouselabweb.org/) or MouseTracker (http://www.mousetracker.org/). Box 2.4 gives an example of a process-tracing approach.

Box 2.4 Inspection patterns of the priority heuristic

The priority heuristic (Brandstätter, Gigerenzer, & Hertwig, 2006) assumes that, rather than calculating SEU, decision-makers follow three rules when making risky choices. The rules (for gains) are:

1. *Priority rule*. Consider the components of a gamble in the following order: minimum gain, probability of minimum gain, maximum gain.
2. *Stopping rule*. Stop examination if the minimum gains differ by 1/10 (or more) of the maximum gain (aspiration level); otherwise, stop examination if probabilities differ by 1/10 (or more) of the probability scale.
3. *Decision rule*. Choose the gamble with the more attractive gain (probability).

Following these rules implies clear-cut and testable process predictions, which have been investigated with reaction time analysis in the original paper, and with attention and search sequence measures by Johnson, Schulte-Mecklenbeck and Willemsen (2008). For instance, the priority rule predicts that information should be acquired in the following order: minimum gain, probability of minimum gain, maximum gain. In conjunction with the stopping rule, it follows that the minimum outcomes will be inspected more often and longer than the maximum outcomes. Johnson et al. (2008) found that attention was actually equally distributed over minimum and maximum outcomes, thus providing no support for the priority and stopping rules. Note, however, that the predictive validity of the priority heuristic for choices is high (Brandstätter et al., 2006).

2.5.2 Heuristics

Ironically, organisms simpler in cognitive architecture may be able to follow the principles of rational choice better (Stanovich, 2013), because the axioms all end up saying, in one way or another, that choices should be unaffected by context, given that complete, well-ordered, and stable preferences exist. Surely, however, your preference for aspirin depends on whether or not you have a headache. That is, aspirin increases happiness only in case of a headache; its value thus is relative. It is a general finding of decision research that most preferences fail to be stable and rather are constructed on the fly (Lichtenstein & Slovic, 2006).

The heuristics-and-biases programme (Gilovich, Griffin, & Kahneman, 2002) deploys the intuition that people do not integrate all available information but use simple rules to navigate the vast amount of information available in the world. The programme developed in Berlin by the ABC Research Group (Gigerenzer, Todd, & the ABC Research Group, 1999), fast and frugal heuristics, argues that heuristics are essential tools to navigate large amounts of information successfully, in their appropriate ecology. In this tradition, heuristics are defined in a stringent and testable manner consisting of three rules: (1) a search rule (defining how search unfolds); (2) a stopping rule (defining when the search stops); and (3) a decision rule (defining how a final decision is made). The fast-and-frugal view takes an idea of Herbert Simon (1955; 1990) seriously, namely that the rationality of a choice not only depends on internal criteria (e.g., following the axioms) but also on the structure of the environment. Rationality is like a pair of scissors – one blade representing the structure of the environment, the other the computational capacities of the person – a proper conceptualization of rationality is only possible by understanding both the person and the environment they act in.

Unlike the SEU model, the heuristic approach does not assume that the organism needs to calculate value. Rather, valuation can be a consequence of simple comparisons, as in the priority heuristic. Decision-by-sampling theory (Stewart, Chater, & Brown, 2006) is exemplary of this approach, modelling decision-making as simple binary, ordinal comparisons. Decision-making works like a pan balance, indicating which of two items is heavier by tipping to one side, while providing no read-out of weight. Direct comparison, rather than value, is fundamental to choice. Reason-based choice is another comparative model, seeing choice as the balance of reasons for and against various alternatives (Shafir & Tversky, 1992). This account of decision-making is typical in the politics of business discourse. Reason-based analyses can explain non-experimental historic, legal and political decisions. In contrast, value-based approaches have dominated experimental research in standard economic analyses. Note that the idea of reason-based choice is very close to the way we normally think and talk about choices, thus providing a natural way to understand the conflict that often characterizes decision-making (i.e., that there are good reasons for and against each option, or conflicting reasons for competing options).

2.5.3 Decisions from Experience

The developments of psychological decision theory, as briefly summed up above, show that people frequently do not follow SEU theory. In contrast, SEU theory neatly predicts the behaviour of animals (e.g., Real, 1996). Where does this difference come from?

First, animal behaviour is tested in real life or at least in elaborate simulations of real life, while humans, by contrast, are tested using abstract analytical models of real life (e.g., lotteries). One such abstraction is to describe probabilities and payoffs to human participants in terms of summary measures (e.g., the probability of an event in the long run: decisions by description) rather than having them find out about the different outcomes of choice alternatives by repeatedly sampling them (decisions by experience). These two modes of decision-making could not be more different: In decisions from description, people get a written or graphical description of a situation, upon which they base their choices. Within this description, value and risk are numerically available and nicely summed up. In decisions from experience, people either need to consult their memory, or to actively sample information from the environment. You might recall from above, that prospect theory predicts, for a description situation, that low probability events are overweighted and high probability events are underweighted. In decisions from experience, the reverse pattern has been found (Hertwig et al., 2004): people behave as if rare events had much less impact than they would objectively deserve. This reverse pattern – the description-experience gap (Hertwig & Erev, 2009) – instigated a research programme of exploring a broad array of questions ranging from decisions in the medical world to the economic domain (for a comprehensive overview, see Wulff et al., 2016). Indeed, only humans have the ability to process abstract, symbolic representations of risky prospects, and animals' decisions are by necessity experience-based. It seems that there are striking similarities between the choices of humans and animals when humans make decisions from experience (Weber, Shafir, & Blais, 2004). This experience side of the *homo economicus* is widely underdeveloped and still neglected in research on risky decision-making.

2.6 HOT DECISIONS

Recently attention in decision research has turned to how emotions and feelings influence judgements and decisions: 'hot' processes became a hot topic. The relationship between affect and decision-making is bilateral, as there is evidence for an impact of affect on decisions (e.g., physiological and psychological arousal changes decisions; Ariely & Loewenstein, 2006), as well as for decisions on affect (e.g., Lerner & Tiedens, 2006) or regret (Connolly & Butler, 2006).

Lerner et al. (2015) identify various themes of affective influences on decision-making. Theme 1 is the integral effect of emotions on decision-making, that is, the effect of emotions that arise directly from the choice at hand. For instance, feeling anxious about a risky outcome may induce the choice of a safer, yet less lucrative, option. Compelling evidence for this type of influence comes from the work of Damasio (e.g., 2006), showing that injuries to the ventromedial prefrontal cortex reduce both patients' ability to feel emotions, and the optimality of their decisions. Many of those patients are risk-prone to the point of bankruptcy. Damasio's somatic marker hypothesis assumes that this is due to patients' inability to experience emotional signals – the somatic markers – that lead healthy people to feel, for example, fear in the presence of high risks. Theme 2 is the influence of incidental emotions. These are emotions unrelated to the decision, having a carry-over effect on choices. For instance, economists have reported a positive correlation between the amount of sunshine and stock market performance (Hirshleifer & Shumway, 2003). Other important themes are emotional influences on the content of thought (e.g., when fear induction leads to increased risk perception; Lerner et al., 2003), and emotional influences on the depth of thought (e.g., when negative mood leads to systematic processing while positive mood leads to heuristic processing; Schwarz, 1996). The interested reader may consult Lerner et al. (2015) for additional themes; here we will concentrate on some focal findings concerning risky decisions.

2.6.1 Predicted Emotions

Quite obviously, the positive or negative outcome of a decision can profoundly affect the decision-maker's feelings after a decision. Research on the consequences of acting unwisely (i.e., regretting a decision) or attaining an unwanted state of affairs (i.e., being disappointed by an outcome) gives testimony of two distinct emotions that may result from experiencing negative outcomes.

People may also experience positive emotions (e.g., joy, pride) following decision-making, though these emotions are only rarely investigated in decision research. The reason for this seems to be that positive emotions have, in contrast to negative emotions, only vague and unspecific action tendencies. According to Fredrickson's (2001) broaden-and-build theory, negative emotions tend to call for specific action tendencies (e.g., flight, or fight) and thus narrow an individual's momentary action repertoire. In contrast, positive emotions broaden an individual's action repertory (e.g., play, explore, savour), since no specific action is called for from experiencing a positive emotion: from feeling good, no specific action follows.

An implicit assumption of research that compares positive to negative emotions is that all positive, or all negative, emotions, are essentially equivalent for decision-making. There is reason to doubt this, since there is evidence that even affective states of the same valence can have distinct influences on decision-making. This is because different positive affective states (e.g., pride vs. cheerfulness), or different negative affective states (e.g., anger vs. sadness), may activate different implicit goals (see also Theme 3 in Lerner et al., 2015).

2.6.2 Risk-as-Feelings and the Affect Heuristic

Schwarz (2000) distinguishes two principled ways in which affect (i.e., weak emotion that is experienced as a quality of 'goodness' or 'badness'), and emotion can influence decision-making: as anticipated emotions (i.e., predictions about the emotional consequences of a decision), or as immediate emotions which are experienced at the time of decision-making. In the risk-as-feeling hypothesis (Loewenstein, Weber, Hsee, & Welch, 2001), risk has a specific affective feature: it is the instinctive and intuitive reaction to danger. Thus, risk is not calculated, but felt – as an immediate visceral reaction (e.g., fear, anxiety, dread). Feelings such as worry, fear, dread, or anxiety can result when people evaluate risky alternatives at a cognitive level. These feeling states can respond to factors that do not enter into cognitive evaluations (e.g., the immediacy of a risk; the vividness with which consequences can be imagined; personal exposure to or experience with the risk), leading to emotional reactions to risks that can diverge from cognitive evaluations of the same risks.

Slovic et al. (2002) have used the term 'affect heuristic' to characterize reliance on such feelings. The idea that current affect has an important role in decision-making, independent of cognitively mediated consequential deliberations, is also central to the affect heuristic. The affect heuristic proposes that the representations of choice situations in people's minds are tagged to varying degrees with affect. In the process of making a judgement or decision, people consult or refer to an 'affect pool' containing all the positive and negative tags consciously or unconsciously associated with the representations. Just as imaginability, memorability, and similarity serve as cues for probability judgements (e.g., the availability and representativeness heuristics), affect may serve as a cue for many important judgements (Slovic et al., 2007).

Thus, this heuristic is a cognitive short-cut that allows quick decisions based on current, negative, but also positive, affect. It is the equivalent to 'going with your gut' – note the similarity to Damasio's somatic marker hypothesis.

Research on risk perception offers a nice example of the affect heuristic. In general, it is true for hazardous activities that risk and benefit are positively correlated (i.e., high-risk activities have greater benefits than low-risk activities). This is not necessarily true for how people understand this correspondence: risk and benefit are often perceived as being negatively correlated. This inverse relationship between perceived risk and perceived benefit is mediated by affect: if I feel uneasy with, say, nuclear power, I tend to consider it a technology of high risk, and at the same time, a technology offering little benefit (Finucane et al., 2000). Thus, affect has informational value. The affect-as-information model (Schwarz & Clore, 1996) is another well-known example of this principle. However, in high levels of emotion, the direct effect is detrimental as it overrides cognition: individuals are 'out of control' (Loewenstein, 1996), acting against their own self-interest. These direct effects also vary depending on the qualitative character of the emotion, that is, the different action-tendencies evoked by different emotions.

Especially interesting are the indirect effects of current emotions on changing expectation and valuation. For instance, people become optimistic when in a good mood (e.g., Bower, 1991). Recent research has shed some light on specific effects of being emotional on the way that people deal with numbers, and on how they evaluate magnitudes. Two such effects, scope insensitivity, and hot-cold empathy gaps, will be discussed next.

2.6.3 Scope Insensitivity

Valuation depends on whether people are in a 'feeling', or a 'calculative' thought mode. Valuation by calculation is a process that relies on some sort of algorithm (e.g., the typical price of a piece of music) that takes into account the nature of the stimulus (e.g., that the piece is performed by the Vienna Philharmonic Orchestra), and its scope (e.g., that an offer contains two symphonies with 15 pieces each). In contrast, valuation by feeling relies on a gut feeling about the stimulus (e.g., that one likes music played by the Vienna Philharmonic Orchestra), but ignores its size (e.g., makes no difference between offers including one symphony or two). The general idea is that when people rely on valuation by feeling, they are sensitive to only basic differences in scope (i.e., the presence or absence of a stimulus) but are largely insensitive to further variations of scope (e.g., three, five or eight items all become 'some'). In contrast, when people rely on calculation, they show sensitivity to scope (Hsee & Rottenstreich, 2004).

Size insensitivity due to affective valuation, that is, the assessment of preference based on the sign and intensity of the emotional response can also exist when evaluating probability. For instance, Rottenstreich and Hsee (2001) asked participants for their willingness-to-pay for either a 1% or 99% chance of winning a $500 coupon, which could be used either for tuition payments (affect-poor) or towards expenses associated with a vacation (affect-rich). At 1%, people were willing to pay more for the vacation coupon than for the tuition coupon, but at 99% the picture reversed. People thus were more sensitive to the variation in probability between 1% and 99% when the prize was affect-poor than when it was affect-rich. In terms of prospect theory, the distinction between valuation by calculation and valuation by feeling translates into different forms of the value and the probability weighting functions. Both functions show more curvature under valuation by feeling.

Thinking in the calculative mode can have important consequences in real life: it can make people less receptive to other people's suffering. Slovic (2007) has described such a process – psychic numbing – in which thinking about large numbers of suffering humans leads to insensitivity towards the number of people involved, and thus mitigates emotional reactions to the suffering others. Indeed, as the number of suffering individuals becomes excessively high – as in genocide, mass famine, or other large-scale crisis – emotions can dissipate to a degree that people become less emotionally responsive to a large-scale as compared to a small-scale suffering.

2.6.4 Empathy Gaps

Predicting future feelings following from a decision can be especially difficult if these feelings are different from the current feelings. Such situations are called empathy gaps (e.g., Loewenstein, 2004) and come in two variants: (1) intrapersonal empathy gaps (predicting how one would feel in a different situation); (2) and interpersonal empathy gaps (predicting how others would feel). With respect to emotion, empathy gaps have two generic forms: hot-to-cold empathy gaps, and cold-to-hot empathy gaps. In hot-to-cold empathy gaps, people who are in emotional (i.e., hot) states tend to underestimate the extent to which their predicted preferences are under the influence of their present emotional state. They tend to underappreciate the influence of transient affect and thus overestimate the stability of their own current preferences. In cold-to-hot empathy gaps, people are not currently affectively aroused, but have to predict their behaviour in arousing situations. People then tend to underestimate the motivational forces of their own future hot states, and thus often fail to self-control. The classic example of a cold-to-hot empathy gap is substance abuse. The failure to empathize with future affective states due to alcohol abuse, or smoking, for instance, will cause decision-makers to underweigh the future consequences of those behaviors. Empathy gaps can specifically influence situations that involve intense emotions like fear, anxiety, or pain, thus, many medical decisions pertain to this category.

2.7 SUMMARY

Theories of economic decision-making have two bedrock concepts: value and risk. Theoretical work focused on ideas how to combine these two to arrive at sound decisions. This work culminated in the formulation of axioms that enable the measurement of utility, and the description of the ideal: the *homo economicus*, who seeks to maximize subjective expected utility. Subsequent empirical work revealed numerous instances where people fall short of this ideal: frequently they neither act in accordance to the axioms, nor maximize utility. Much of this research comes under the heading of 'heuristics'. However, interpretations differ, emphasizing either the negative (i.e., biased and irrational), or the positive (i.e., ecologically rational) consequences of relying on heuristics. In addition, directly investigating the process of decision-making, rather than merely its result, led to a wealth of interesting new findings that informed the development of new models, not following the expectancy-value structure. Finally, it became obvious that decision-making is not a purely cognitive process. Rather, emotional and affective influences are integral features, mediating and moderating the whole process of economic decision-making. These developments inform a new understanding of rational decision-making as a blend of cognitive and emotional processes that result in adaptive choices, dependent on the characteristics of the chooser, the context, and the relationship between chooser and context.

REVIEW QUESTIONS

1. What is the idea of expected utility theory? Explain in words and formula.
2. Explain the idea of the risk-as-feeling model.
3. Decisions-by-description versus decisions-by-experience: Discuss relevant similarities and differences in experimental operationalization and empirical findings.
4. How do emotion and affect interact with cognition? Explain the interaction for the case of magnitudes.

REFERENCES

Allais, M. (1953). Le comportement de l'homme rationnel devant le risque: Critique des postulats et axiomes de l'école américaine. *Econometrica: Journal of the Econometric Society*, 503–546.

Altman, M. (2004). The Nobel Prize in behavioral and experimental economics: A contextual and critical appraisal of the contributions of Daniel Kahneman and Vernon Smith. *Review of Political Economy*, *16*, 3–41.

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*, 87–98.

Bernoulli, D. ([1738] 1954). Exposition of a new theory on the measurement of risk. (Ed. & Trans.) *Econometrica*, *22*(1), 23–36. DOI:10.2307/1909829.

Bower, G. H. (1991). Mood congruity of social judgment. In J. Forgas (Ed.), *Emotion and social judgment* (pp. 31–54). Oxford: Pergamon Press.

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

Caplin, A., & Glimcher, P. W. (2014). Basic methods from neoclassical economics. In P. W. Glimcher, & E. Fehr (Eds.), *Neuroeconomics* (2nd ed.; pp. 3–17). New York: Elsevier.

Connolly, T., & Butler, D. (2006). Regret in economic psychological theories of choices. *Journal of Behavioral Decision Making*, *19*, 139–154.

Damasio, A. R. (2006). *Descartes' error* (2nd ed.). New York: Random House.

Davidson, D., McKinsey, J. C. C., & Suppes, P. (1955). Outlines of a formal theory of value, I. *Philosophy of Science*, 140–160.

Dreher, J-C. (2007). Sensitivity of the brain to loss aversion during risky gambles. *Trends in Cognitive Sciences*, *11*, 270–272.

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*, 1–17.

Fredrickson, B. F. (2001). The role of positive emotions in positive psychology. *American Psychologist*, *56*, 218–226.

Gigerenzer, G., Todd, P. M., & the ABC Research Group (1999). *Simple heuristics that make us smart*. New York: Oxford University Press.

Gilovich, T., Griffin, D., & Kahneman, D. (Eds.). (2002). *Heuristics and biases*. New York: Cambridge University Press.

Hacking. I. (1983). *Representing and intervening: Introductory topics in the philosophy of natural science*. New York: Cambridge University Press.

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*, 534–539.

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

Hirshleifer, D., & Shumway, T. (2003). Good day sunshine: Stock returns and the weather. *The Journal of Finance*, *58*, 1009–1032.

Hsee, C. K., & Rottenstreich, Y. (2004). Music, pandas, and muggers: On the affective psychology of value. *Journal of Experimental Psychology: General*, *133*, 23–30.

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*, 263–272.

Kahneman, D., Knetsch, J. L., & Thaler, R. H. (1991). Anomalies: The endowment effect, loss aversion, and status quo bias. *The Journal of Economic Perspectives*, *5*, 193–206.

Kahneman, D., Slovic, P., & Tversky, A. (Eds.). (1982). *Judgment under uncertainty: Heuristics and biases*. New York: Cambridge University Press.

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

Kahneman, D., & Tversky, A. (1982). Variants of uncertainty. *Cognition*, *11*, 143–157.

Knetsch, J. L., & Sinden, J. A. (1984). *Willingness to pay and compensation demanded: Experimental evidence of an unexpected disparity in measures of value*. *The Quarterly Journal of Economics*, *99*, 507–521.

Knight, F. H. (1921). *Risk, uncertainty, and profit*. New York: Hart, Schaffner & Marx.

Kogler, C., Kühberger, A., & Gilhofer, R. (2013). Real and hypothetical endowment effects when exchanging lottery tickets: Is regret a better explanation than loss aversion? *Journal of Economic Psychology*, *37*, 42–53.

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*, 144–150.

Lerner, J. S., Li, Y., Valdesolo, P., & Kassam, K. S. (2015). Emotion and decision making. *Annual Review of Psychology*, *66*, 799–823.

Lerner, J. S., & Tiedens, L. Z. (2006). Portrait of the angry decision maker: How appraisal tendencies shape anger's influence on cognition. *Journal of Behavioral Decision Making*, *19*, 115–137.

Lichtenstein, S., & Slovic, P. (Eds.). (2006). *The construction of preference.* New York: Cambridge University Press.

Loewenstein, G. F. (1996). Out of control: Visceral influences on behavior. *Organizational Behavior and Human Decision Processes*, *65*, 272–292.

Loewenstein, G. F. (2004). Hot-cold empathy gaps and medical decision making. *Health Psychology*, *24*, 49–56.

Loewenstein, G. F., Weber, E. U., Hsee, C. K., & Welch, N. (2001). Risk as feelings. *Psychological Bulletin*, *127*, 267–286.

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

Real, L. A. (1996). Paradox, performance, and the architecture of decision-making in animals. *American Zoologist*, *36*, 518–529.

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

Samuelson, W., & Zeckhauser, R. (1988). Status quo bias in decision making. *Journal of Risk and Uncertainty*, *1*, 7–59.

Savage, L. J. (1954). *The foundations of statistics*. New York: Wiley.

Schulte-Mecklenbeck, M., Kühberger, A., & Ranyard, R. (Eds.). (2011). *A handbook of process tracing methods for decision research: A critical review and user's guide*. London: Psychology Press.

Schwarz, N. (2000). Emotion, cognition, and decision making. *Cognition and Emotion*, *14*, 433–440.

Schwarz, N., & Clore, G.L. (1996). Feelings and phenomenal experiences. In E. T. Higgins & A. Kruglanski (Eds.), *Social psychology: Handbook of basic principles* (pp. 433–465). New York: Guilford.

Shafir, E., & Tversky, A. (1992). Thinking through uncertainty: Nonconsequential reasoning and choice. *Cognitive Psychology*, *24*, 449–474.

Simon, H. A. (1955). A behavioral model of rational choice. *Quarterly Journal of Economics*, *69*, 99–118.

Simon, H. A. (1990). Invariants of human behavior. *Annual Review of Psychology*, *41*, 1–19.

Slovic, P. (2007). 'If I look at the mass I will never act': Psychic numbing and genocide. *Judgment and Decision Making*, *2*, 79–95.

Slovic, P., Finucane, M. L., Peters, E., & MacGregor, D. G. (2002). The affect heuristic. In T. Gilovich, D. Griffin, & D. Kahneman (Eds.), *Heuristics and biases: The psychology of intuitive judgment* (pp. 397–420). New York: Cambridge University Press.

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

Smith, D. V., & Huettel, S. A. (2010). Decision neuroscience: Neuroeconomics. *Wiley Interdisciplinary Reviews: Cognitive Science*, *1*, 854–871.

Stanovich, K. E. (2013). Why humans are (sometimes) less rational than other animals: Cognitive complexity and the axioms of rational choice. *Thinking & Reasoning*, *19*, 1–26.

Stewart, N., Chater, N., & Brown, G. D. (2006). Decision by sampling. *Cognitive Psychology*, *53*, 1–26.

Tannert, C., Elvers, H-D., & Jandrig, B. (2007). The ethics of uncertainty. *EMBO Reports*, *8*, 892–896.

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

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

von Neumann, J. V., & Morgenstern, O. (1944). *Theory of games and economic behavior.* Princeton, NJ: Princeton University Press.

Weber, E. U., Shafir, S., & Blais, A-R. (2004). Predicting risk sensitivity in humans and lower animals: Risk as variance or coefficient of variation. *Psychological Review*, *111*, 430–445.

Wulff, D. U., Mergenthaler, M., & Hertwig R. (2016). A meta-analytic review of two modes of learning and the description–experience gap. (Manuscript under review).

FURTHER READING

Caplin, A., & Glimcher, P. W. (2014). Basic methods from neoclassical economics. In P. W. Glimcher, & E. Fehr (Eds.), *Neuroeconomics* (2nd ed.; pp. 3–17). New York: Elsevier.

Johnson, J. G., & Busemeyer, J. R. (2010). Decision making under risk and uncertainty. *Cognitive Science*, *1*(5), 736–749.

Lerner, J. S., Li, Y., Valdesolo, P., & Kassam, K. S. (2015). Emotion and decision making. *Annual Review of Psychology*, *66*, 799–823.