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The Psychology of Risk Management

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The Psychology of Risk Management

Risk lies at the heart of the most common banking decisions. Large banks have retail, commercial, and investment banking operations. The nature and magnitude of the risks, and potential returns, vary considerably across these different operations. A general characterisation of risk involves two dimensions: the extent of harm caused by an adverse outcome (e.g., a bank run, a large commercial client declaring bankruptcy, significant fluctuations in the availability of credit) and the likelihood that this adverse outcome will occur (Breakwell, 2007). For the past two decades, major investment firms have managed those risks by using complex mathematical models for measuring risk in various portfolios. Those models were used to quantify risk positions, often in the form of a Value-at-Risk (VaR), which corresponds to the maximum potential loss that could be expected with a 99% or 95% probability. These mathematical models have also been criticised, however, for not taking into account the possibility of "black swans," those extremely rare outcomes which could lead to a thousand fold increase in losses, such as those witnessed in the recent economic downturn and credit crisis (Taleb, 2007). In the face of those dramatic events, some financial analysts have argued that the crumbling of large financial institutions was due, in part, to “risk mismanagement” and called for a shift from decisions based on formal modelling to decisions based on more subjective degrees of beliefs about the uncertain future (Nocera, 2009).

There is, however, an essential element missing from these discussions: the inherent human factor involved in risk management and decisions under uncertainty. No matter how sophisticated they can be, quantitative risk estimates are only as good as the parameters human risk managers chose to include in their mathematical models. No matter how reliable they may be, those estimates are one of many factors that will determine whether investors will elect to expose themselves to greater risks in the hope of greater returns or whether they will reduce their risk exposure to guard against harmful losses. A better understanding of how these human factors may shape risk perception and risk taking is key to improve investment performance. This chapter will draw on research on the psychology of risk and decision-making under uncertainty to shed light on these issues. The first part will focus on the evaluation of risk and uncertainty. After outlining the different psychological concepts of uncertainty, we will review the different factors influencing individuals' subjective perception of risk as well as the heuristics they may use to gauge risk and uncertainty. The second part of this chapter will focus on the different factors influencing human risk-taking behaviour, ranging from attitudes to risk to the contexts in which risky decisions take place, and the role of emotions in risk taking.

Part 1: Assessing and Perceiving Risks

The psychological study of risk originated in research efforts to operationalise the mathematical axioms of expected utility theory introduced by von Neumann and Morgenstern and later developed by Savage in the late 1950s (Slovic, Fischhoff, & Lichtenstein, 1982). Since, concerns about risk have become ubiquitous as they have substantial operational consequences in many private organisations and public institutions. High-profile disasters and forecast failures (e.g., the Challenger space shuttle launch, the foot-and-mouth disease crisis in British agriculture, Enron, the 9/11 attacks) drive the demand for better risk management. Stakeholders and the public's growing expectations for control and manageability in the face of uncertainty motivate the development of risk assessment and risk management practices in clinical, health, political, legal, as well as financial settings (Power, 2007).

The prevalence of risk concerns across these different organisational and institutional contexts also contributes to make risk a multi-faceted, at times controversial, concept that is used and interpreted in a variety of ways by different stakeholders. In the domain of health and safety, for example, risk is synonymous of hazard or ‘danger from future damage’ (Joffe, 2003) and is sometimes defined as a multi-dimensional index encompassing the different potential consequences of hazards faced by workers or general members of the public, such as the relative proportion of deaths, non fatal injuries and illnesses that may occur, the concern over the extent to which the consequences of these hazards are fully known, and the feelings of dread they may evoke in potential victims (Fischhoff, Watson, & Hope, 1984). Within the financial realm, risk refers to a technical concept associated with the assessment of the volatility of expected gains and losses (Power, 2007).

A finance industry standard for measuring credit risk, market risk and operational risk is the VaR measure (Law & Smullen, 2008). VaR is usually defined as the loss of a portfolio over a specific period of time, which is expected to occur with a set degree of probability under ‘normal’ circumstances (Choudry, 2006). For example, a company’s assets with a daily VaR of £1 million to a 99% confidence level has (only) a 1% chance of losing more than £1 million over the next 24 hours. The results of VaR modelling are often believed to represent a relatively easy way for senior management in financial institutions to understand and visualise enterprise risk exposure. A critical feature of the VaR measure for our purpose, however, is its probabilistic nature; it is not a certain prediction. To estimate the VaR, analysts must establish the probability distribution of likely returns for the asset or portfolio under consideration and senior management must understand the probabilistic meaning of VaR. The first step in taking a psychological perspective on risk management is therefore to revisit the concept of probability and its psychological meaning.

The Psychological Meaning of Uncertainty

Appraising how individuals interpret and understand the multi-faceted concept of probability is a critical issue for the psychologist studying risk and uncertainty judgements. A psychological probability (ψ) is a concept that is distinct from the concept of probability defined by mathematicians or philosophers (Vail, 1954). Kolmogorov's concept of mathematical probability (μ) is defined by four mathematical axioms independently of any interpretational framework (Von Plato, 1994). The two main philosophical frameworks[1] for defining the meaning of probabilities are Von Mises's (1928/1957) Frequentist framework and De Finetti's (1937/1964) and Ramsey's (1931/1964) Subjectivist framework. Within the Frequentist framework, an objective probability (*f*) is conceived as the relative frequency of a target outcome, established using an objective method for recording its occurrence and its failure to occur. In contrast, according to the Subjectivist framework, probabilities (β) are theoretical degrees of belief associated with the different possible outcomes of an event. Unlike *f* probabilities, β probabilities are not uniquely determined. The same independent body of evidence may give rise to different degrees of belief in the occurrence of an outcome or in the truth of a proposition. Both β and *f* probabilities, however, are subjected to the same mathematical axioms defining μ probabilities.

Psychological probabilities, by contrast, represent opinions about past, present or future events. Three different types of psychological probabilities can be distinguished (Vail, 1954): ψμ or the *perception of* μ, ψ*f* or the *perception of f* and finally, ψβ or a *degree of confidence*. Unlike μ, β, or *f* probabilities, ψ probabilities are not constrained by Kolmogorov's mathematical axioms. ψμ probabilities are determined by μ but also by the description of the particular event *E*, whose μ is judged. These probabilities are not estimated but rather computed from existing probabilities. By contrast, ψ*f* is conceived as the impression of the relative frequency of an event. As such, ψ*f* may arise from witnessing the repetitive occurrence of a finite outcome, from an introspective, experienced-based judgement of the strength of the association between the event and a particular outcome (Kahneman & Tversky, 1982/1982d), or else, from the use of (quasi) analytical rules whose

[1] There exist still other philosophical interpretations of probabilities, such as the Logical framework developed by Keynes or the Propensity approach developed by Popper (see, e.g., Gillies, 2000).

appropriateness is determined by the extent of individuals' grasp of the probability calculus (Teigen, 1994). In any case, ψf relies on distributional evidence, either consciously or associatively perceived, and reflects, more or less accurately, uncertainty in the *outside* world (Lagnado & Sloman, 2004). Finally, $\psi\beta$ corresponds to the degree of confidence in an event's occurrence or truth and may be informed by a conscious computation of μ, the perception of f, as well as some other sources of information such as the examination and balancing of evidence (Kahneman & Tversky, 1982) or the examination of the properties of an option as a mean to predict the probability of its success. These latter two sources of information reflects an *inside* view of uncertainty which relies on singular evidence to evaluate the probability of an event (Lagnado & Sloman, 2004).

When it comes to risk management, we can assume, in all likelihood, that the mathematical and statistical sophistication of risk managers and the analytical tools they use will ensure that their perception of μ and of f (i.e., $\psi\mu$, and ψf, respectively) will be fairly accurate. But, ultimately, it is unlikely that their final subjective evaluation of risk relies solely on those sources of information. Risk analysis requires the exercise of judgment from experts and even the provision of objective probabilities cannot warrant the objectivity of the final judgment (Fischhoff, Watson, & Hope, 1984). Thus, $\psi\beta$, the subjective perception of the probability of an event is unlikely to be solely informed by μ or f. In fact, both laypersons and professionals are susceptible to form judgments which deviate from the prescriptions of the Kolmogorov axioms, depending on the type of the uncertain event considered and how this event is described, as well as their past experience and prior knowledge, the format of the information presented, their mindset or even the context of evaluation varying time and social pressure (Philips, 1970; Vail, 1954). In other words, even if risk assessments are informed by very objective perceptions of μ and f, this does not guarantee that the final degree of belief,

$\psi\beta$, will be as accurate and unbiased.[2] In the following section, we will review those factors susceptible to affect psychological degrees of beliefs and we will show how they may exert such an influence.

The Malleability of Risk and Uncertainty Perception

The value of our risk and uncertainty judgements is subjected to a variety of subtle influences. In this subsection, we review some of these influences and their effects on judgments, ranging from the format of the likelihood information, the partitioning of events, the type and positive or negative valence of the risky outcome, and the scales made available to anchor judgments.

Risk perception may vary dramatically as a function of the format in which likelihood information is presented. Thus, Slovic, Monahan, and McGregor (2000, Experiment 3) asked 479 clinicians in practice to rate the risk of violence posed by a patient, based on a psychologist's evaluation of the likelihood that the patient will commit an act of violence against others in the first months after his discharge from inpatient hospitalisation. The researchers manipulated the psychologist's likelihood judgements along two dimensions: the level of probability communicated (10% or 20%) and the format in which this likelihood statement was presented. Specifically, they compared probability statements (e.g., "Patients similar to Mr Jones are estimated to have a 10% probability of committing an act of violence") with frequency statements relative to small samples (e.g., "Of every 10 patients similar to Mr. Jones, 1 is estimated to commit an act of violence") or larger samples (e.g., "Of every 100 patients similar to Mr. Jones, 10 are estimated…"). As Figure 1 illustrates, the use of frequency formats consistently led to a higher proportion of practitioners believing that the patient posed a medium or high risk of violence.

[2] In fact, as pointed out in many of the chapters in this volume, in practice it is even unrealistic, if not impossible, to estimate the 'objective' measures of risk μ or f due to model and measurement uncertainty.

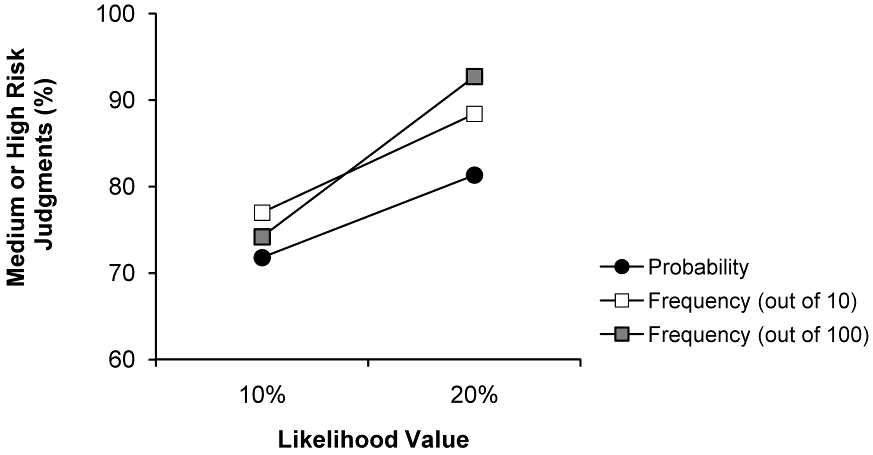

Figure 1. The effect of information format on perceived risk. Based on Slovic et al.(2000, Experiment 3).

In a similar vein, the partition of events may influence the perceived likelihood that a target event is true. For example, Fischhoff, Slovic and Lichtenstein (1978) asked experienced car mechanics to estimate the probabilities that an engine's failure to start was caused by a number of deficiencies. The experts judged that there was a 23% chance that the problem was due to the fuel system when this potential cause was presented alongside three other deficiency categories (i.e., alongside 'battery', 'engine' and 'other'). When, however, fuel system was one of seven categories of deficiencies proposed (i.e., alongside 'battery', 'starting system', 'ignition system', 'engine', 'mischief' and 'other'), the car mechanics' subjective probability that this particular deficiency was causing the failure dropped to 10%. This effect, also known as the 'pruning bias' has been replicated in different contexts ranging from estimating the probability of different causes of death (Tversky & Koehler, 1994; Harries & Harvey, 2000) or the probability of different MBA programs being ranked #1 in the next *Business Week* survey (Fox & Clemen, 2005). Moreover, although increasing domain knowledge may lessen the pruning bias, it does not eliminate it (Fox & Clemen, 2005; Harries & Harvey, 2000).

Subjective beliefs in the likelihood that an outcome will occur have also been shown to vary as a function of the type of risky outcome under consideration. Thus, more severe or dangerous events are often also judged to be more likely. For example, the perceived risk of taking a drug may depend on the severity of the drug's side effects. Respondents in a study by Fischer and Jungermann (1996) considered that it was less risky to take a drug that would *occasionally* lead to mild side effects, such as headaches or lack of appetite, than taking a drug that would *occasionally* lead to severe side effects, such as impaired vision or impaired hearing, despite the fact that the base-rate of occurrence of these side effects was identical in both conditions. Similarly, in a forensic context, subjective degrees of belief in the truth of a statement were significantly higher when respondents were told that an offender was *likely* to kill again compared to when they were told that the offender was *likely* to return to the crime scene, despite the fact that both statements were characterised by the same level of likelihood (Villejoubert, Almond, & Alison, 2009).

In some instances, this severity effect may be explained by the dynamics of risk communication. Thus, in a medical setting, respondents' likelihood judgments were also strongly influenced by their interpretation of a doctor's communicative intentions (Bonnefon & Villejoubert, 2006). Specifically, respondents who believed the doctor was being polite when telling them they would "possibly" suffer from a severe (deafness) or milder (insomnia) medical condition also believed that they would almost certainly develop the condition. In contrast, those who believed that the doctor was merely communicating his uncertainty when qualifying the outcome as a possibility were comparatively less certain they would develop the condition. More generally, this effect can be explained by the asymmetry of losses entailed by underestimating as opposed to overestimating the probability of an adverse outcome (Harris, Corner, & Hahn, 2009; see also Weber, 1994). Accordingly, underestimating the probability that a harmful outcome may arise (and failing to engage in preventive behaviours) may carry greater costs than overestimating such a probability. For example, a company that underestimates the probability that it would incur a large loss where such loss was controllable (for example, by hedging exposure to a liability) may potentially face more acute consequences than if it had overestimated the probability of loss in the first instance.

This suggests that the severity bias would be especially pronounced for outcomes that are both potentially harmful and controllable. Recent empirical research (Harris et al., 2009, Experiment 3) provided support for this hypothesis by showing that participants held higher subjective degrees of belief in the occurrence of an adverse outcome (e.g., the potentially lethal fall of plane debris occurring during RAF training) when they were also believed that one could act in order to avoid potential harms (e.g., when the RAF was not restricted in its choice of air space).

The positive or negative framing of an uncertain outcome can also affect the subjective perception that this outcome will occur. In particular, individuals may exhibit an optimistic bias whereby an outcome with a given objective base rate of occurrence will be judged more likely to happen if it has a positive valence (e.g., winning) rather than a negative one (e.g., losing). Lench and Ditto (2008, Experiment 2) asked participants to play a card game where a computer presented a card face down, drawn from a deck of 10 cards with varying proportion of winning and losing cards. Participants were nearly four times more likely to predict that the card was a winning card than a losing card. For example, 97% participants believed that the card drawn was a winning card when told that 6 out of 10 cards in the deck were winning cards. By contrast, only 68% participants believed a losing card had been drawn when told that 6 out of 10 cards in the deck were losing cards.

In a similar vein, research has shown that outcomes that appear to be more salient than others was sufficient to lead respondents to believe this outcome was more likely to occur. Bar-Hillel, Budescu and Amar (2008) asked students to express their subjective probability that several football teams would win a match in the World Cup football games. Respondents were also given a separate coupon naming one of the team listed in the questionnaire and were told that they would receive a small cash prize if the team named on the coupon actually won the game (Experiment 1) or they were simply told that the researchers were particularly interested in a given team whose name was printed in bold (Experiment 2). In both experiments, the teams that were highlighted by the experimental manipulation were also believed to be significantly more likely to win the game.

Finally, subjective degrees of belief about the occurrence of an outcome may also be influenced by the scale available to anchor one's estimate. For example, experts' likelihood judgments may vary as a function of the range of values made available to them on a rating scale. In the aforementioned study, Slovic et al. (2000, Experiment 1) also asked forensic psychologists and psychiatrists to estimate the likelihood that patients would harm someone other than themselves in the six months following their discharge from the hospital. When the response scale presented a large array of probabilities ranging from 1% to 100% (1%, 10%, 20%, …, 100%), the experts estimated that there was an average 30.2% probability that patients would cause harm to someone. When, however, the response scale presented a larger set of small probabilities (1%, 2%, 5%, 10%, … 35%, 40%, > 40%), the average probability of harm dropped to 18.2%. This effect was replicated even when likelihood judgments were preceded by a short tutorial on what probabilities are and how they should be estimated prior to the likelihood judgment task (Slovic et al., 2000, Experiment 2). In a similar vein, Fox and Clemen (2005) asked MBA students at Duke University to estimate the probability that the starting salary of a Duke MBA graduate would fall into particular brackets. The salary brackets were either unpacked in the low subranges (i.e., $55,000 or less; $55,001–$65,000; $65,001–$75,000; $75,001–$85,000 vs. more than $85,000) or in the high subranges (i.e., $85,000 or less; $85,001–$95,000; $95,001–$105,000; $105,001–$115,000 vs. more than $115,000). Again, the scale used had a remarkable impact on judgments. When salaries were unpacked using the low subrange scale, the median estimate of the probability that the starting salary would be less than $85,000 was .75. By contrast, the median value of this probability was estimated at .40 by those who were given the high subrange scale to record their judgment. In other words, those who were given a scale that explicitly presented values well above $85,000 formed the impression that salaries would likely start above this cut-out point.

To summarise, the different factors reviewed in this section show that our subjective degrees of belief in the occurrence of uncertain outcomes, $\psi\beta$, are subjected to subtle psychological influences which are independent from the outcome's objective probability of truth or occurrence, μ. When informed by statistics presented in a frequency format, risks of a harmful outcome occurring tend to be deemed higher, compared to risk assessments based on information presented in a probability format. The subjective probabilities associated with a distribution of outcomes will also vary depending on whether possible alternative outcomes have been explicitly specified or merely implicitly evoked. Outcomes themselves can affect subjective probabilities: Individuals may overestimate the likelihood that severe outcomes will occur, especially if those outcomes are controllable (i.e., could be avoided), possibly to encourage the protagonists to engage in risk reducing behaviours. The probability that positive outcomes will occur may also be overestimated, especially if the context makes them salient. Finally, even the way in which judgments are elicited may guide and constrain the perception of uncertainty.

The research reviewed so far points out how external influences may affect the perception or risks and uncertainty. The psychological study of judgments of risk and uncertainty, however, often goes beyond those descriptive accounts to explain how the mind works to estimate uncertainty, thus providing a greater insight in the psychology of risk and uncertainty. The following section reviews this work, and focuses on the heuristics individuals may use to assess uncertainty as well as the role of affect and other cognitive illusions to account for risk and uncertainty judgments.

Gauging Risk and Uncertainty: Heuristics, Biases, and Affect

Four decades ago, pioneer research by Tversky and Kahneman (1974) suggested that subjective beliefs in the occurrence of outcomes were determined by the use of heuristic principles, which simplify the task of assessing uncertainty. These authors compared the subjective assessment of uncertainty to that of physical quantities where data of limited validity are processed heuristically. An object, for example, may be seen with more or less precision, and processed as being more or less distant from the judge, based on the heuristic principle stating that blurry objects tend to be further away from the perceiver. This heuristic principle is often economical and ecologically valid but can also lead to systematic biases in the estimations. Under poor lighting conditions, for example, individuals may overestimate the distance that separates them from a target object, as it will appear blurrier. In a similar vein, Tversky and Kahneman (1974) described three heuristics individuals may use to assess probabilities and the potential biases in judgment that may ensue from using those heuristics: the representativeness heuristic, the availability heuristic, and the anchoring-and-adjustment heuristic.

The *representativeness heuristic*, subsequently recast as the ‘attribute-substitution’ heuristic (Kahneman & Frederick, 2002), consists in assessing an explicit target attribute by substituting a related heuristic attribute that comes readily to mind. For example, instead of assessing the probability that a person is employed in a certain occupation, individuals may assess the similarity of that person with another whom they believe to be typical or representative of that occupation. Although assessing similarity is less taxing in cognitive resources than assessing probabilities and can thus be an efficient way to make judgments, the use of this heuristic is not without shortcomings. For example, using the representativeness heuristic entails the neglect of base rates. Thus, estimates of the probability that a particular individual is an engineer rather than a lawyer should take into account the odds that *any* individual is an engineer rather than a lawyer in the population considered. Yet, those judgments are strongly influenced by how similar to a typical engineer that particular individual appears to be, while the base rate of engineers has a negligible influence on the judgments (Kahneman & Tversky, 1973).

This heuristic may also make individuals insensitive to predictability (Tversky & Kahneman, 1974). Thus, individuals may believe a company will be more likely to make a high profit if this company's description is very favourable and overlook possible shortcomings. A favourable description will make a high profit appear more representative, and therefore influence its estimation of occurrence. As Tversky and Kahneman (1974) pointed out, however, relying solely on favourableness to estimate the likelihood of success may lead to biased judgements if the evidence provided is unreliable. Furthermore, using the representativeness heuristic may also create an illusion of validity. Specifically, when the outcome predicted is deemed highly representative of the possible outcomes of a given event, individuals will also be highly confident that their prediction is accurate, even though the information used to assess the representativeness of the outcome may be unreliable. In all likelihood, this illusion of validity will operate in risk reporting where senior management is provided with risk information about a company's situation without any information about measurement or model uncertainty. Lacking such crucial information for assessing the reliability of the risk estimate will almost certainly accentuate decision-makers' confidence that the risk estimate presented is accurate.

The illusion of validity or overconfidence encompasses different judgment biases (Moore & Healy, 2008). The most prevalent illustration of overconfidence is the tendency to overestimate one's actual performance (e.g., on a quiz test), or the level of control over the occurrence of a particular outcome in a chance task and consequently one's likelihood of success, especially on difficult tasks. For example, chance situations that resemble skill situations because they are familiar, involving, or embedded in a competitive context, may lead people to act as if their actions can influence the outcome of a chance event. This illusion of control consequently leads them to increase their perceive likelihood of successfully predicting the outcome. Thus, Langer (1975) showed that participants who competed against an ill-at-ease player tended to bet almost twice as much in a chance game than participants who competed against a self-assured player (see Thompson, Armstrong, & Thomas, 1998 for a review).

Another heuristic, which may be relied upon when assessing subjective beliefs, is termed the *availability heuristic* (Kahneman & Tversky, 1973). The availability heuristic consists in using the ease with which instances are conjured up in memory as a basis for estimating their probability of occurrence. For example, one may evaluate the likelihood that a company will incur a given loss based on how easy or difficult it is to imagine that this company would face various difficulties in the near future.

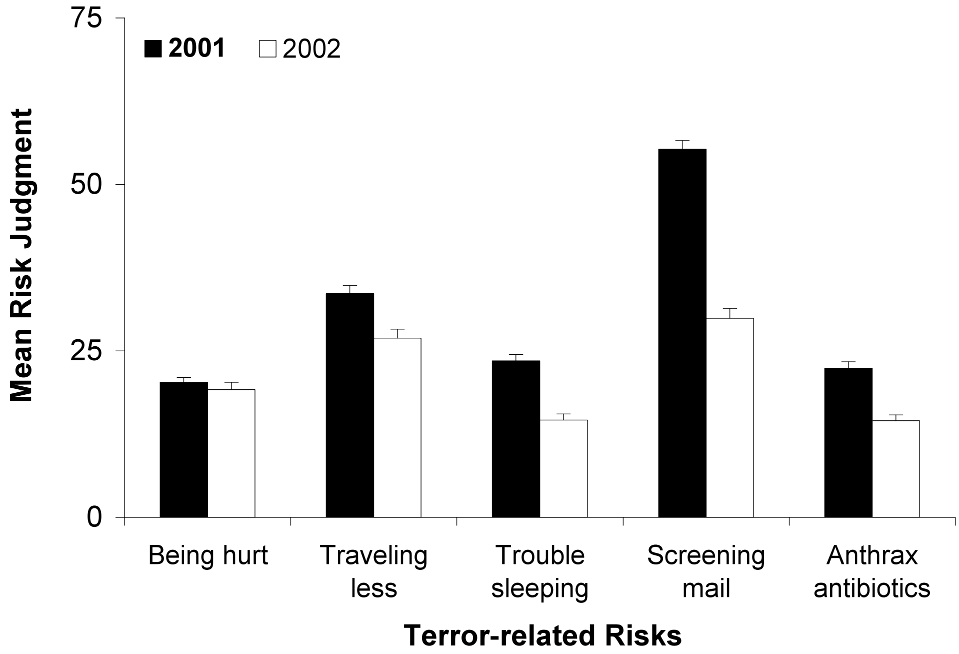

Figure 2. Subjective terror-related risk judgments in 2001 and 2002. Based on Fischhoff, Gonzalez, Lerner, and Small (2005). Error bars represent standard errors.

Like the representativeness heuristic, the availability heuristic may be an advantageous strategy to estimate probabilities since people are more likely to recall easily outcomes that are actually more frequent. But, once more, the use of this strategy is not without shortcomings. For example, more familiar or more salient outcomes such as recent news may also be easier to remember but familiarity or saliency may not necessarily be correlated with frequency (unlike, less familiar or salient information such as long-term averages). For example, Fischhoff, Gonzalez, Lerner, and Small (2005) asked a large sample of individuals to judge the probability that five terror-related risks would occur in the next 12 months at the end of 2001 during the anthrax crisis and the Afghanistan campaign and, again, at the end of 2002, at a time when the U.S. news focused on smallpox vaccination, the inspection of Iraq and the Mombasa and Bali attacks. As Figure 2 illustrates, by 2002, most risks were perceived to be smaller, especially the perceived risks related to an Anthrax attack. These results thus clearly illustrate how more salient events may lead to dramatic rises in risk perception. When the Anthrax crisis was at its peak of media coverage, perceived risks of

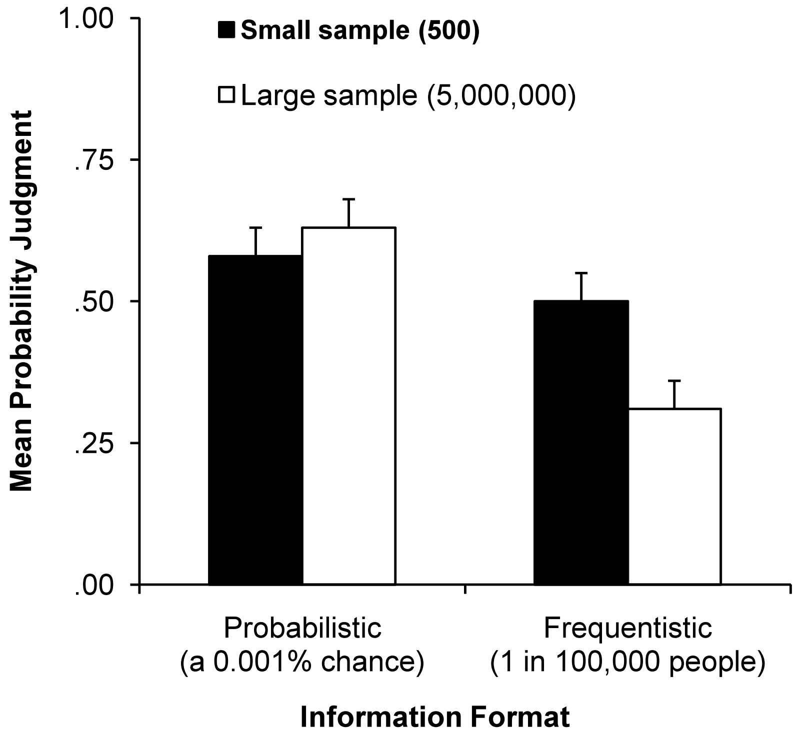

Figure 3. The effect of exemplar cuing on probability judgments. Based on Koehler and Macchi (2004, Experiment 1). Error bars represent standard errors.

mail attacks were also heightened. Availability may also affect judgments through the ease with which outcomes can be imagined. Tversky and Kahneman (1974) suggested that risks that are difficult to imagine may be underestimated. For example, research has shown that the format of statistical information may affect judgements by facilitating or, on the contrary, hindering the representation of concrete exemplars of an uncertain event. This fact was demonstrated in a legal decision-making context where respondents were asked to estimate the subjective probability that a suspect was the source of blood drops found on a crime scene, ψ(Source), based on a DNA-matching statistic that indicated the frequency of DNA profile found at the crime-scene among humans (Koehler & Macchi, 2004). As Figure 3 illustrates, results showed that ψ(Source) judgments remained above the 50% chance level when the DNA-matching statistic was presented in a probabilistic format referring to a single target, as in "*The chance* that *the suspect* would match the blood drops if he were not their source *is* 0.001%" (Koehler & Macchi, 2004, p. 542, italics added).

These judgments, however, were significantly lower when respondents were cued to represent alternative exemplars of individuals whose DNA may match that of the blood drops. To illustrate this point, Koehler and Macchi (2004) compared the impact of DNA-matching statistics presented in a frequentistic format referring to multiple targets, as in “1 in 100,000 *people in a town* who are not the source would nonetheless match the blood drops,” (Koehler & Macchi, 2004, p. 542, italics added) in contexts which either hindered or cued the mental representation of alternative exemplars. Thus, when applying the 1 in 100,000 frequency to a small sample size (500 inhabitants), respondents’ ψ(Source) judgment remained high. Koehler and Macchi (2004) argued that this was because respondents could not imagine a single individual other than the suspect matching the sample (since 0.01‰ of 500 is less than one). When, however, respondents had the opportunity to apply the DNA-matching statistic to a larger sample size (5,000,000 inhabitants), their ψ(Source) judgment was significantly lower. According to the authors, this is because exemplars of individuals who could provide a matching sample were easily brought to mind (since 0.01‰ of 5,000,000 is more than one). Overall, exemplar-cuing research suggests that individuals will be more receptive to low-probability events when the statistical description of these events’ likelihood readily evokes concrete exemplars.

The final heuristic highlighted by Kahneman and Tversky (1973) was the *anchoring-and-adjustment heuristic*. Judgments arising from the use of this heuristic are based on an initial value (the anchor), which is then adjusted to produce a final judgment. The adjustment, however, is generally insufficient. For example, when assessing subjective probability distributions of a quantity such as the Dow-Jones average on a given day, individuals may first anchor their thoughts on their best estimate and then adjust this estimate downward or upward to provide the lower and upper limits of a confidence interval (Kahneman & Tversky, 1973). The anchor need not be relevant to the judgment at hand to have an effect. For example, minimum selling prices for a lottery ticket can be strongly correlated with an arbitrary initial anchor derived from judges' social security number (Chapman & Johnson, 1999).

Kahneman and Tversky's heuristics emphasize how mental shortcuts may change the way information is handled which can consequently lead to biased judgments. As such, these heuristics are cognitive in nature: they relate to the acquisition, manipulation, and communication of knowledge. Although they are often studied in the laboratory, they may also have impact on real-life major events. Thus, Haldane (this volume) suggests that, as memory of the failure of the hedge fund LTCM in September 1998 faded, agents who used the availability heuristic as a basis for their subjective probability judgement would start underestimating the probability of a forthcoming financial crisis (akin to the individuals whose perception of terror-related risks probability decreased as a function of time in Fischhoff et al.'s 2005 study). As such, the availability heuristic may have been in part responsible for the "disaster myopia" which contributed to the credit boom of the Golden Decade and its subsequent bust.

Cognitive heuristics may not explain all, however. Recent research has pointed out the need to complement the cognitive perspective on uncertainty judgments and risk assessments with an affective perspective, which aims to understand how emotions and affect influence these evaluations. Thus, Finucane, Alhakami, Slovic and Johnson (2000) proposed that judgments are guided by images marked with positive or negative affective feelings. Accordingly, individuals may rely on an *affect heuristic* to make risk assessments, whereby they substitute the evaluation of the likelihood of an outcome with that of the overall affective impression evoked by the outcome. Outcomes that evoke positive affective impressions are judged as more beneficial and less risky.

In a similar vein, affect has been shown to play a significant role in financial forecasting. Thus, a study by MacGregor, Slovic, Dreman and Berry (2000) revealed that images evoked by the names of different industry groups influenced financial forecasting. Up to three thoughts or images associated with particular industry groups (e.g., clothing and shoe chains, food distributors, etc.) were elicited from students enrolled in an investment-banking course alongside polarity ratings for those images (ranging from highly negative to highly positive). For each industry group, students were then asked to judge three performance criteria including how likely they would be to buy shares of a new company belonging to the industry group under consideration. Results revealed that the average image rating for each industry group was a strong predictor of all the performance criteria judged. For example, it explained 31% of the variance in students' judgments of the likelihood that they would buy shares in an Initial Public Offering (IPO) of a group's company whereas the actual levels of performance for each industry group explained a mere 6% of the variance in the IPO likelihood judgments.

To summarise, research has demonstrated that the use a variety of mental shortcuts or heuristics to assess risks and uncertainties is ubiquitous. Although these heuristics can be cost effective in terms of mental efforts, they can also bias assessments and predictions in a systematic way. Even if senior risk managers anchor their risk assessments on 'objective' estimates such as the VaR, the research reviewed here also strongly suggests that their personal risk assessment, or $\psi\beta$, will nevertheless be affected by heuristic processing. As Finucane (2002) justly pointed out, taking into account the psychological richness of risk perception and risk assessment is a crucial initial step for gaining a better understanding of finance and investment decision-making under risk and uncertainty. Thereafter, a second step would consists in better understanding how perceived risks relate to such decisions. Accordingly, the remainder of this chapter will review the insights from psychological research regarding the factors that may promote or prevent risk taking in decisions under risk and uncertainty.

Part 2: Taking Risks

Taking risks amount to choosing an alternative that may lead to rewards but also to losses or harm. According to Subjective Expected Utility (SEU) Theory (von Neuman & Morgenstern, 1944; see also Nau, 2007, for a recent review), risky decisions involve the consideration of alternatives X_i with different possible consequences or outcomes x_j, which can be experienced (e.g., positive or negative emotions, personal satisfaction or discontentment), or received (e.g., monetary gains and losses). Those outcomes are characterised by their subjective probability of occurrence, $p(x_j)$ or p_j and their utility or subjective value for the decision-maker, $u(x_j)$ or u_j. Thus, each risky alternative X_i can be characterised by its overall expected value, defined as the sum of the subjective utilities associated with each alternative outcomes multiplied by their respective subjective probability of occurrence, as outlined by the following equation:

$$U(X_i) = \sum_{i=1}^{n} u(x_j) \cdot p(x_j) = \sum_{i=1}^{n} u_j \cdot p_j$$

Under this framework, a rational decision-maker will compare the expected value of each decision alternative available and will choose the alternative with the highest expected value, in an attempt to maximise the utility she might receive or experience from her choice. Psychological research, however, has identified many instances in which individuals' choices deviate from the prescriptions of SEU theory.

'Irrational' Influences

There are several principles defining rational choice that can be drawn from the assumption of SEU theory. A notable example is the principle of invariance, according to which choice preferences should remain stable across logically equivalent versions of decision alternatives (Arrow, 1982). For example, if outcome $X_1(u_1, p_1)$ is preferred to X_2 (u_2, p_2), then $X_1(u_1, p_1/k)$ should also be preferred to $X_2(u_2, p_2/k)$. Yet, it is now well established individuals will have a strong preference for a sure gain over a probable one but that preference will be easily reversed if both gains are uncertain; this is referred to as the certainty effect. For example, Kahneman and Tversky (1979) found that 78% of individuals interrogated preferred a one-week tour of England with certainty over a 50% chance of winning a three-week tour of England, France and Italy; however, when asked to choose between a 5% chance of touring England for a week and a 10% chance of touring England, France, and Italy for three weeks, 67% of respondents now preferred the latter option. Yet, according to SEU theory, if X_1 = {England}, $p_1 = 1$ is preferred to X_2 = {England ∩ France ∩ Italy}, $p_2 = .50$ then X_1' = {England}, p_1' = .10 should also be preferred to X_2' = {England ∩ France ∩ Italy}, p_2' = .05.

The certainty effect implies that individuals are risk-averse in the domain of gains, since they prefer a sure gain to a probable one. The reflection effect illustrates a mirror pattern of preferences in the loss domain. For example, 92% individuals preferred an 80% chance of losing £4,000 over a sure loss of £3,000; however, this preference for the first option disappear when individuals are asked to choose between a 20% chance of losing £4,000 and a 25% chance of losing £3,000 (Kahneman & Tversky, 1979). These findings therefore suggest that certainty or near-certainty will intensify the aversive value of negative outcomes but increase the attractive value of positive outcomes.

Such deviations from SEU prescriptions led to the development of alternative descriptive models, such as Prospect theory (Kahneman & Tversky, 1979), which assumes that people do not objectively compare the final states of wealth represented by potential outcomes to decide among risky alternatives. Instead they register those outcomes as gains and losses defined relative to a neutral point of reference. This reference point may be dictated by the decision-maker's current asset position or by the way in which the alternatives are presented. The effect of the way decision information is presented on risky choice is known as "framing" (Tversky & Kahneman, 1981; see also Maule & Villejoubert, 2007, for a more recent review). The effect of framing on risk preference in the financial domain was illustrated in Roszkowski and Snelbecker (1990) with the following two problems administered to financial services professionals (the square brackets indicate the percentage of participants who expressed a preference for each strategy):

> Problem 1: Imagine that your client has $6000 invested in the stock market. A downturn in the economy is occurring. You have two investment strategies that you can recommend under the existing circumstances to preserve your client's capital.
>
> If strategy A is followed, $2,000 of your client's investment will be saved. [60%]
>
> If strategy B is followed, there is a one-third probability that the entire $6,000 will be saved, and a two-third probability that none of the principal will be saved. [40%]
>
> Given this information, which of these two strategies would you favor?

The majority of respondents presented with this problem were risk-averse: the prospect of saving a portion of their client's investment was more attractive than a risky prospect with an identical expected value ($6,000 × 1/3 = $2,000). A second group of financial services professionals were given the same problem except that the cover story was now framed in terms of losses:

> Problem 2: Imagine that your client has $6000 invested in the stock market. A downturn in the economy is occurring. You have two investment strategies that you can recommend under the existing circumstances to preserve your client's capital.
>
> If strategy A is followed, $4,000 of your client's investment will be lost. [38%]
>
> If strategy B is followed, there is a one-third probability that nothing will be lost, and a two-third probability that the $6,000 will be lost. [62%]
>
> Given this information, which of these two strategies would you favor?

The majority of respondents presented with the loss version of this simple choice task now preferred the risky option, suggesting that the sure loss of $4,000 is less acceptable than the two-third probability of losing the entire principal. Moreover, Roszkowski and Snelbecker (1990) found no effect of level of expertise on this preference reversal and concluded that dealing daily with financial risk was not enough to render choices immune to the effect of framing on risk-taking.

Loss aversion and the use of reference points are not limited to behaviours observed in the laboratory. Shapira and Venezia (2001) analysed a large sample of randomly selected investment transactions and showed that professional investors are subject to a disposition effect when making transactions: they tend to hold on stocks with decreasing values for almost twice as long than stocks with increasing values.

Contextual Influences

Risk preferences and risk taking can also be influenced by context. For instance, the order in which information about a simple lottery is presented can affect individuals' evaluations. Thus, when presented with an hypothetical lottery offering a $200 prize with a .025 probability of winning, MBA students judged that the $200 prize was more valuable and the .025 probability represented a better chance of winning when told about the prize before rather than after being told about the probability of winning (Bond, Carlson, Meloy, Russo, & Tanner, 2007). The order of presentation of information related to risky choices may also influence choices where the decision-maker has no predefined preferences and initial information is used to shape tentative dispositions towards one decision alternative or another. In this case, information presented after the initial information during the decision process can be "distorted" to support such an emerging disposition (Russo & Yong, in press). In fact, recent research has also demonstrated that both probability and outcome information may be subject to such distortions so that they are perceived as favouring the preferred alternative (DeKay, Patiño-Echeverri, & Fischbeck, 2009).

Risk preferences also depend on the task domain (gain vs. loss) and on the probability of the outcome (small or medium vs. large or certain). Extending Prospect theory (Kahneman & Tversky, 1979), Cumulative Prospect theory (Tversky & Kahneman, 1992) proposed that risk-averse and risk-seeking preferences were a direct consequence of individuals' tendency to overweight small probabilities and to underweight medium and large probabilities in choices between gambles. Specifically, people should prefer the risky alternative to the sure outcome with identical expected value, when small or medium probabilities are associated with large gains (e.g., 1% chance of winning £7500 vs. a sure gain of £75) and when large probabilities are associated with small losses (e.g., 60% of losing £125 vs. a sure loss of £75). Alternatively, they should prefer the sure outcome when small or medium probabilities are associated with large losses (e.g., 1% chance of losing £7500 vs. a sure loss of £75) and when large probabilities are associated with small gains (e.g., 60% of winning £125 vs. a sure gain of £75).

Preferences may also vary as a function of the type of decisions considered. Kusev, Van Schaik, Ayton, Dent and Chater (2009) distinguished between gambling decisions in abstract monetary-gamble situations, such as those outlined above, and precautionary decisions, such as decisions about insurance concerned with risk reduction. Specifically, precautionary decisions where shown to lead to a greater propensity of risk aversion in the domain of losses, especially when large probabilities were associated with small losses, contrary to the predictions of Cumulative Prospect theory. Thus, whereas a majority of individuals would prefer, say, a 60% chance of losing £125 compared to a sure loss of £75, the same individuals would also prefer to pay £75 to insure against the loss of their £125 luggage rather than have a 60% chance of losing them.

Time pressure is another contextual factor that can sway risk preferences. Ben-Zur and Breznitz (1981) presented two alternatives with identical expected values in a gambling task under different conditions of time pressure. Respondents could choose between a lottery offering a high probability of winning a small amount (risk-averse choice) and a lottery offering a low probability of winning a large amount (risk-seeking choice). Respondents who

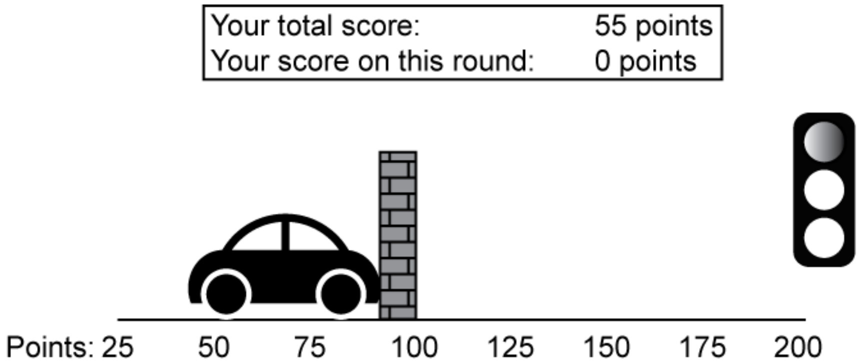

Figure 4. Illustration of the Chicken video game. Participants had to stop the car before the traffic light turned red otherwise a wall appeared to signify the crash of the car and they lost all the points accumulated in the round. Adapted from Gardner & Steinberg (2005).

were forced to make a choice under high time pressure (in less than 8 seconds) were more likely to choose the safer lottery compared to those under medium or high time pressure (16 and 32 seconds, respectively). These results suggest that choices with uncertain options with equal expected values made under severe time pressure will enhance individuals' aversion for risks.

Decisions involving risks are rarely taken in isolation. Dealing with risks in the presence of others, however, can also affect risk preferences. For example, when playing a computer-simulated roulette game, participants who were given information about the wins and losses of previous players tended to make more risky wagers than participants who played without knowing how other players performed in the past (Martinez, Le Floch, & Gaffié, 2004). Similarly, Rockloff and Dyer (2006) explored how learning about others' wins while one is playing with an electronic gambling machine may influence risk-taking. The researchers found that players who both heard and saw information about others' wins during a play were more likely to leave the game with no money, played a larger number of trials and gambled at a lower pace that those who were not aware of others' concurrent performance.

Others may also influence the decision-maker with their advice: Gardner and Steinberg (2005) asked individuals to play the so-called Chicken video game, which required to decide whether or not to stop a car moving across the computer screen before a traffic light turned red. Participants' reward was contingent on the distance travelled by the car on each round of the game, provided that they had stopped the car before the light turned red. If the car was still moving when the light turned red, all the points accumulated in the current run were lost (see Figure 4 for an illustration). Adults paired with an observer who proffered advice took more risks than those who played alone.

Emotional Influences

For a long time, the psychological study of risk has favoured a consequentialist perspective on risk-taking presuming that individuals make risky decisions based on a more or less accurate evaluation of the severity and likelihood of the outcomes of each possible choice alternative. Within this framework, risk-taking was viewed as a thoughtful, analytical activity, which remained essentially independent of passion and emotion. In contrast to this traditional view, Loewenstein, Weber, Hsee, and Welch (2001) proposed to distinguish between anticipatory and anticipated emotions in risk taking. The former emotions are instantaneous visceral reactions to risk and uncertainty such as fear, anxiety and dread one may experience at the time of making a risky choice (Bechara, 2004). The latter are prospective emotions that are not experienced while taking a risky decision but, instead, are expected to arise at a later point in time, when the risk taker will experience the outcome of his or her decision. Such anticipated emotions include the disappointment and regret individuals might experience if their choice turns out to be detrimental (Mellers, Schwartz, Ho, Ritov, 1997; Mellers, Schwartz, & Ritov, 1999). In this final subsection, we briefly review the effect of these two classes of emotions on risk preferences and choices.

The role of anticipatory emotions in risk taking was first illustrated by neuropsychologists studying patients presenting lesions in a region located at the front of the cerebral hemispheres. Most intellectual abilities (e.g., memory or problem-solving skills) of these patients were preserved, with the exception of activities pertaining to planning and choice (Bechara, Tranel, & Damasio, 2000). The study of these patients led to the development of the somatic marker hypothesis (Damasio, 1994). According to this hypothesis, the brain associates the memory of the option chosen with the memory of the emotions triggered by the outcomes experienced upon making a risky choice. Thereafter, presentations of a similar option give rise to the previously learnt emotional response (or "somatic markers") before a choice is made. This emotional 'hunch' thus serves to guide decisions under uncertainty. To test this hypothesis, Bechara, Tranel and Damasio (2000) designed a gambling task where individuals were asked to pick a card from one of two decks. Unbeknownst to the participants, one deck led to large immediate gains ($100) but larger future losses ($1250 every ten cards on average) whereas the other deck yielded small immediate gains ($50) but smaller future losses ($250 on average). As the number of rounds progressed, participants quickly learnt to favour the advantageous deck. The researchers also recorded participants' skin conductivity responses[3] (SCRs). Results showed that participants' SCRs first increased after they experienced gains and losses. With experience participants began to produce anticipatory SCRs before selecting a card, even if they were unable to articulate the relative probabilities of gains and losses in the two decks, in line with the predictions of the somatic marker hypothesis.

As mentioned above, risk preferences and choice may also be influenced by emotions individuals anticipate they will experience when they will learn the outcome of a risky decision (Mellers & McGraw, 2001). For example, when pondering over two possible risky courses of action, individuals may consider how regretful or how glad they would feel after experiencing the outcome of one decision by comparing that outcome to the outcome they would have most likely experienced had they made the alternative choice (Bell, 1982;

[3] The skin conductivity response is a change of the levels of sweat linked to a change in emotions.

Loomes & Sugden, 1982). Thus, Simonson (1992) investigated the effect of anticipated regret on consumers' risky decisions. The researcher asked marketing and psychology students to imagine they were about to buy various products for their personal use. For each product category, respondents were faced with a choice between two alternatives: a more expensive item manufactured by a well-known company (e.g., a Panasonic VCR) and a cheaper alternative manufactured by an unknown company (e.g., a SounDesign VCR). Both products were described as offering the same technical characteristics but the information about their respective reliability was unavailable. Results showed that respondents who were simply asked which product they would prefer to buy were equally likely to prefer the safe alternative (the expensive well-known brand) or the riskier one (the cheaper unknown one). By contrast, respondents who were first asked to reflect on how regretful they would feel if they learnt the well-known brand turned out to be better or equivalent to the unknown one before making a choice, were more likely to choose the safer alternative (the expensive, albeit well-known brand). As such, these results suggested that the consideration of anticipated regrets might sway preferences towards more risk-averse decisions.

Considerations of regret, however, may also lead to an increase in risk seeking behaviours in situations were the option which minimises regret happens to be the riskier one (Zeelenberg, 1999). For example, Zeelenberg and Beattie (1997) asked university students to evaluate a safe and a risky financial option. Participants were told they had inherited £1,000 and were faced with two options to invest the money for the next five years: a Government Bond and a High Interest Account which would respectively pay back between £1,000 and £1,800 or between £1,250 and £1,350 after the 5-year period, respectively. Half the participants were asked to imagine, in addition, that they would ultimately learn how well the Government Bond would perform since their sister had already invested her own share of the inheritance in this scheme and would let them how much she earned at the end of the 5-year period. The remaining half of participants, by contrast, was simply told about the two investment options and could only expect to learn the outcome of the option they had chosen. Results showed that participants expecting feedback on the riskier option were more likely to choose that option. Those, on the other hand, who only expected to receive feedback on their own choice were more likely to choose the safer option. Thus, this research demonstrates that if people can expect to learn what the outcome of the riskier choice will be, they will be more likely to choose that option in order to avoid feeling regretful about choosing the safer option and learning that the riskier choice was more profitable.

To summarise, this brief review of risk taking has revealed that, contrary to rational expectations, risk preferences will vary as a function of the reference point used to evaluate risky outcomes as gains or losses. Because individuals tend to be risk averse in the domain of gains and risk seeking in the domain of losses, they may exhibit reversed preferences for otherwise logically equivalent sets of choice alternatives, as illustrated by the certainty effect, the reflection effect and the framing effect. Moreover, risk taking may be amplified or attenuated by seemingly irrelevant contextual factors such as whether information about uncertainty precedes or follows information about choice outcomes, whether they relate to risk-reduction or gambling situations, or whether decisions are taken under time pressure. Similarly, knowing about others' past or current outcomes in risky situations or simply hearing what others' would do at the time of deciding may affect one's choice or risk preferences. Finally, moving beyond the traditional consequentialist perspective on risk taking where risky choice results from the thoughtful consideration of probability and outcome utility, recent research has also established the important role of emotions in guiding risky choice. Accordingly, research has established that anticipatory emotions may inform risky decisions and this with a relative degree of conscious awareness at the moment of making a decision.

Conclusions

The research reviewed in this chapter illustrates how psychology provides an insightful window onto financial analysts' and managers' risk perception and risk taking. Since risk management is ultimately a human activity, regarding it as a mathematical exercise detached from human emotions and cognitive preferences is potentially misguided and can, ultimately, prove costly. Whereas risk management will undoubtedly be informed by quantitative considerations such as VaR measures, we argued that such information is but one source of influence on final risk perceptions and risk decisions. A better understanding of risk management in financial settings and, ultimately, a better management of risks will likely emerge from a better understanding of the role played by the various psychological factors described in this chapter. For example, the research demonstrating that the information format of presentation affects risk perception suggests that VaR measures may have different impact on managers depending on the way they are communicated. Thus, providing information about the maximum deviation between the predicted loss and the actual loss in the form of a value associated with a high level of confidence (95% or 99%) may convey a false sense of certainty and control. Conveying the same information with frequencies may help managers make more realistic psychological assessments of the risks actually incurred.

The psychological studies of risk reviewed in this chapter have been carried out in a variety of domains, which may be more or less closely related to that of financial risk management. Likewise, this chapter also illustrated that the methods used to study risk perceptions and risk taking are numerous and varied. Many of the contexts and situations studied, however, can be transposed to the financial sphere. The task facing players of the chicken video game under peer and time pressure (see Fig. 4 above), for instance, could be seen as analogous to the task facing market investors who must decide when to shift strategy for a particular stock (e.g., from holding to selling) in the presence of peers contemplating similar decisions. Finally, by the very nature of their trade and occupational reputation, risk managers may be reluctant to participate in the decision scientist's research. Future research efforts on financial risk management in real-life settings, however, will offer a sounder platform from which to identify the contextual and psychological variables that contribute to better risk assessments and decisions under risk.

References

Bar-Hillel, M., Budescu, D. V., & Amar, M. (2008). Predicting World Cup results: Do goals seem more likely when they pay off? *Psychonomic Bulletin & Review*, *15*, 278-28.

Bechara, A. (2004). The role of emotion in decision-making: evidence from neurological patients with orbitofrontal damage. *Brain and Cognition*, *55*, 30-40.

Bechara, A., Tranel, D., & Damasio, H. (2000). Characterization of the decision-making impairment of patients with bilateral lesions of the ventromedial prefrontal cortex. *Brain, 123*, 2189–2202.

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

Ben-Zur, H. & Breznitz, S. J. (1981). The effect of time pressure on risky choice behavior. *Acta Psychologica, 47*, 89-104.

Bond, S. D., Carlson, K. A., Meloy, M. G., Russo, J. E., & Tanner, R. J. (2007). Information distortion in the evaluation of a single option. *Organizational Behavior and Human Decision Processes*, *102*, 240-254.

Bonnefon, J.-F., & Villejoubert, G. (2006). Tactful or doubtful? Expectations of politeness explain the severity bias in the interpretation of probability phrases. *Psychological Science*, *17*, 747-751.

Chapman, G., & Johnson, E. (1999). Anchoring, activation, and the construction of values. *Organizational Behavior and Human Decision Processes*, *79*, 115-153.

Choudry, M. (2006). *An introduction to Value-at-Risk* (4th ed.). Chichester, UK: John Wiley & Sons.

Damasio, A. R. (1994). *Descartes' error: Emotion, reason, and the human brain*. New York: Grosset/Putnam.

De Finetti, B. (1964). Foresight: Its logical laws, its subjective sources. In H. E. Kyburg & H. E. Smokler (Eds.), *Studies in subjective probability* (pp. 93-158). New York: John Wiley & Sons. (Original work published 1937)

DeKay, M. L., Patiño-Echeverri, D., & Fischbeck, P. S. (2009). Distortion of probability and outcome information in risky decisions. *Organizational Behavior and Human Decision Processes*, *109*, 79-92.

Finucane, M. L. (2002). Mad cows, mad corn, & mad money: Applying what we know about the perceived risk of technologies to the perceived risk of securities. *Journal of Behavioral Finance*, *3*, 236-243.

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.

Fischer, K., & Jungermann, H. (1996). Rarely occurring headaches and rarely occurring blindness: Is rarely = rarely ? *Journal of Behavioral Decision Making*, *9*, 153-172.

Fischhoff, B., Gonzalez, R., Lerner, J., & Small, D. (2005). Evolving judgments of terror risks: Foresight, hindsight, and emotion. *Journal of Experimental Psychology: Applied*, *11*, 124–139.

Fischhoff, B., Slovic, P., & Lichtenstein, S. (1978). Fault trees: Sensitivity of estimated failure probabilities to problem representation. *Journal of Experimental Psychology: Human Perception and Performance*, *4*, 330–344.

Fox, C. R., & Clemen, R. T. (2005). Subjective probability assessment in decision analysis: Partition dependence and bias toward the ignorance prior. *Management Science*, *51*, 1417-1432.

Gardner, M., & Steinberg, L. (2005). Peer influence on risk taking, risk preference, and risky decision making in adolescence and adulthood: an experimental study. *Developmental psychology*, *41*, 625-35.

Gillies, D. A. (2000). *Philosophical theories of probability*. London: Routledge.

Harries, C., & Harvey, N. (2000). Are absolute frequencies, relative frequencies, or both effective in reducing cognitive biases? *Journal of Behavioral Decision Making*, *13*, 431-444.

Harris, A. J., Corner, A., & Hahn, U. (2009). Estimating the probability of negative events. *Cognition*, *110*, 51-64.

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

Kahneman, D., & Tversky, A. (1982). Variants of uncertainty. In D. Kahneman, P. Slovic & A. Tversky (Eds.), *Judgement under uncertainty: Heuristics and biases*. (pp. 509-520). Cambridge, UK: Cambridge University Press.

Koehler, J., & Macchi, L. (2004). Thinking about low-probability events: An exemplar-cuing theory. *Psychological Science*, *15*, 540-547.

Lagnado, D., & Sloman, S. A. (2004). Inside and outside probability judgment. In D. J. Koehler & N. Harvey, *Blackwell Handbook of Judgment and Decision Making* (pp. 157-176). Oxford, UK: Blackwell Publishing.

Law, J., & Smullen, J. (Eds.). (2008). Value-at-risk. *A dictionary of finance and banking.* Oxford, UK: Oxford University Press.

Le Floch, V., Martinez, F., & Gaffié, B. (2004). Announcing results for others in a game of chance: A second point of reference? *Canadian Journal of Behavioural Science, 36*, 310-320.

Lench, H. C., & Ditto, P. H. (2008). Automatic optimism: Biased use of base rate information for positive and negative events. *Journal of Experimental Social Psychology*, *44*, 631-639.

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

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

MacGregor, D., Slovic, P., Dreman, D., & Berry, M. (2000). Imagery, affect, and financial judgment. *The Journal of Psychology and Financial Markets*, *1*, 104-110.

Maule, J., & Villejoubert, G. (2007). What lies beneath: Reframing framing effects. *Thinking & Reasoning, 13*, 25-44.

Mellers, B. A., & McGraw, A. P. (2001). Anticipated emotions as guides to choice. *Current Directions in Psychological Science*, *10*, 210-214.

Mellers, B., Schwartz, A., & Ritov, I. (1999). Emotion-based choice. *Journal of Experimental Psychology: General*, *128*, 332–345.

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

Moore, D. A., & Healy, P. J. (2008). The trouble with overconfidence. *Psychological Review, 115*, 502-517.

Nau, R. F. (2007). Extensions of the subjective expected utility model. In W. Edwards, R. J. Miles, & D. von Winterfeldt, *Advances in decision analysis: From foundations to applications* (pp. 253-278). Cambridge, UK: Cambridge University Press.

Nocera, J. (2009, January 2). Risk mismanagement. *The Times Magazine*. Retrieved from http://www.nytimes.com

Kusev, P., van Schaik, P., Ayton, P., Dent, J., & Chater, N. (2009). Exaggerated risk: prospect theory and probability weighting in risky choice. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *35*, 1487-1505.

Phillips, L. D. (1970). The "true probability" problem. *Acta Psychologica, 34*, 254-264.

Power, M. (2007). *Organized uncertainty: Designing a world of risk management.* Oxford: Oxford University Press.

Ramsey, F. P. (1964). Truth and probability. In H. E. Kyburg & H. E. Smokler (Eds.), *Studies in subjective probability* (pp. 61-92). New York: John Wiley & Sons. (Original work published 1931)

Rockloff, M. J., & Dyer, V. (2007). An experiment on the social facilitation of gambling behavior. *Journal of Gambling Studies*, *23*, 1-12.

Roszkowski, M., & Snelbecker, G. (1990). Effects of "Framing" on measures of risk tolerance: Financial planners are not immune. *Journal of Behavioral Economics*, *19*, 237-246.

Russo, J. E., & Yong, K. (in press). The Distortion of Information to Support an Emerging Evaluation of Risk. *Journal of Econometrics*.

Shapira, Z., & Venezia, I. (2001). Patterns of behavior of professionally managed and independent investors. *Journal of Banking & Finance*, *25*, 1573-1587.

Simonson, I. (1992). The influence of anticipating regret and responsibility on purchase decisions. *Journal of Consumer Research*, *19*, 105.

Slovic, P., Monahan, J., & MacGregor, D. G. (2000). Violence risk assessment and risk communication: The effects of using actual cases, providing instruction, and employing probability versus frequency formats. *Law and Human Behavior*, *24*, 271-96.

Taleb, N. N. (2007). *The black swan: The impact of the highly improbable*. New York: Random House.

Teigen, K. H. (1994). Variants of subjective probabilities: Concepts, norms, and biases. In G. Wright & P. Ayton (Eds.), *Subjective probability* (pp. 211-238). Oxford, United Kingdom: John Wiley & Sons.

Thompson, S. C., Armstrong, W., & Thomas, C. (1998). Illusions of control, underestimations, and accuracy: a control heuristic explanation. *Psychological Bulletin, 123*, 143-61.

Tversky, A., & Kahneman, D. (1992). Cumulative prospect theory: An analysis of decision under uncertainty. *Journal of Risk and Uncertainty, 5*, 297-323.

Tversky, A., & Koehler, D. J. (1994). Support theory: A nonextensional representation of subjective probability. *Psychological Review*, *101*, 547–566.

Vail, S. (1954). Alternative calculi of subjective probabilities. In R. M. Thrall, C. H. Coombs & R. L. Davis (Eds.), *Decision processes* (pp. 87-98). Oxford, United Kingdom: John Wiley & Sons.

Villejoubert, G., Almond, L., & Alison, L. (2009). Interpreting claims in offender profiles: the role of probability phrases, base-rates and perceived dangerousness. *Applied Cognitive Psychology*, *23*, 36-54.

Von Mises, R. (1957). *Probability, statistics and truth*. London: Allen & Unwin. (Original work published 1928)

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

Von Plato, J. (1994). *Creating modern probability: Its mathematics, physics and philosophy in historical perspective*. Cambridge: Cambridge University Press.

Weber, E. U. (1994). From subjective probabilities to decision weights: The effect of asymmetric loss functions on the evaluation of uncertain outcomes and events. *Psychological Bulletin*, *115*, 228-242.

Zeelenberg, M. (1999). Anticipated regret, expected feedback and behavioral decision-making. *Journal of Behavioral Decision Making*, *12*, 93-106.

Zeelenberg, M., & Beattie, J. (1997). Consequences of regret aversion 2: Additional evidence for effects of feedback on decision making. *Organizational Behavior and Human Decision Processes, 72*, 63-78.