UNIVERSITY OF OXFORD
Institute for New Economic Thinking
AT THE OXFORD MARTIN SCHOOL

THE SCIENCES OF RISK: IMPLICATIONS FOR REGULATION OF THE FINANCIAL SECTOR

BACKGROUND LITERATURE REVIEW FOR THE WORKSHOP ON BEHAVIOUR, RISK AND REGULATION, 3RD JULY 2013

3rd July 2013

INET Oxford Working Paper No. 2013-01

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INTRODUCTION

Can insights from a starling's foraging behaviour help bank's identify which customers are most likely to repay their loans? To prevent another financial crisis, will regulators need to understand how testosterone affects young men? Are policy makers applying behavioural insights naively? The overall objective of this paper is to bring together different insights gained from the study of risk in a range of scientific disciplines, to provide the background reading necessary to start the discussion on how insights from these diverse empirical and theoretical approaches may be applied to answer major outstanding issues in financial regulation and policy.

Surveying such a diversity of literatures necessarily requires a brief discussion of definitions. The more quantitative disciplines (e.g. economics, engineering) define 'risk' objectively as the probability of an event occurring, multiplied by its magnitude, and 'uncertainty' (sometimes referred to as ambiguity) as the accuracy by which the risk can be assessed[1]. The magnitude of the event in question, determines how hazardous it is. However, these definitions are not recognised in every discipline. In particular, sociological studies deliberately reject this definition and argue that risk is a subjective human construct, which only exists when humans have a stake in the outcomes[1,2]. A subjective measurement of risk incorporates an individual's emotions, beliefs, background and culture. This conception of risk is so intimately related to uncertainty, that the former incorporates the latter. The sociological view of risk argues that people do not perceive an event as risky unless there is some degree of uncertainty about the future. For simplicity, wherever possible, this review sticks with the objective definitions of risk, even if the specific literatures surveyed would not use these terms in the ways used here.

The review necessarily begins with biology. Humans are a product of natural selection and much of our behavioural predispositions that help us cope with risk and uncertainty may be understood as adaptations that helped us survive in past environments. Section 1 introduces the biological literature on risk in both humans and non-human species and discusses the conceptual differences between evolutionary and economic theories. There are many aspects of human behaviour which set us apart from other animals, in particular our culture, language and cognitive abilities. Thus biological theories can only take us for far; section 2 surveys the rich diversity of social science disciplines, and summarises both theoretical and empirical literatures relevant to risk behaviour in humans. Insights from all these disciplines generate relevant policy insights. Section 3 considers the current practical applications of behavioural work, and describes the use of behavioural insights in policy.

SECTION 1: BIOLOGICAL SCIENCES

Imagine you are watching a bird searching in the grass for food. An interested observer may start asking themselves questions about the bird's behaviour. Why did it choose to forage on that particular piece of grass? How does it decide when it's safe to be out in the open? If it fails to find food, how long does it keep looking before trying somewhere else? Within biology, the discipline of behavioural ecology provides the framework to answer risky questions such as these (i.e. ones involving choices where outcomes are variable). In the social sciences, the dominant framework to answer such questions is provided by economic models of decision-making. Despite their apparent similarities, economics and evolutionary biology have fundamentally different axiomatic foundations.

Before discussing these theoretical differences, it is relevant to note that behavioural ecologists seek both proximate and ultimate explanations for animal behaviour. The proximate perspective is concerned with developmental explanations, such as whether and how the behaviour is learnt or the degree to which it is genetically hard-wired, and mechanistic explanations for the behaviour, for example in terms of the nervous system, brain activity, hormonal and skeleto-muscular control. Developmental and mechanistic studies provide proximate explanations, because they explain how an individual comes to behave the way it does during its lifetime. The ultimate perspective, in contrast, is concerned with adaptive, or functional explanations for the behaviour, and seeks to understand *why* the individual evolved to behave that way. Proximate and ultimate explanations are complementary, and are developed in consort. A complete understanding of behaviour is only possible when both perspectives are considered.

The first part of this section focuses on the ultimate, evolutionary, explanations for animal behaviour; it introduces evolutionary theory and explores the differences between biology and economic approaches (part 1). The second part shows how the biological approach has been used to study questions that involve risk in non-human species (part 2) and the third part, reviews some of the current work that is providing proximate explanations for risk-related behaviours in humans (part 3).

1.1. Economic vs Evolutionary rationality

Evolutionary explanations, with their 'fitness maximizing' language, appear to bear strong parallels with economic explanations. However, despite their common theoretical forms, rationality in economics and biology are epistemologically very different (referred to henceforth as B-rationality and E-rationality respectively[3]). Evolutionary biologists do not consider E-rationality important when studying behaviour. Nevertheless, the B-rationality logic, which is derived from evolutionary biology, underpins the study of decision-making in animals and plants and is as central to biological thinking as utility is to economics. This section introduces economic rationality (1), and biological rationality (2), describe how optimality models are used to study animal behaviour (3) and explain why animals are not expected to behave B-rationally all the time (4).

1.1.1. Economic rationality

In theoretical microeconomics, E-rationality does not emerge as a result, in the way B-rationality does in evolutionary biology, but instead, it is a necessary assumption for the development of predictive models. In economics, rationality concerns the internal coherence of an individual's choices. It assumes that individuals have well-defined, stable preferences (i.e. given a variety of choices, an individual knows which option they prefer) and that individuals are able to rank different sets of alternatives, in order of preference. Thus an individual either has a preference or is perfectly indifferent i.e. considers the options equally attractive.

In order for an economist to apply optimality theory to study how people (or animals) make decisions, several assumptions are needed. First, to define preferences using a single measure – utility – requires that preferences are complete (i.e. all actions can be ranked in order of preference), transitive (not circular) and independent (if the choice set is expanded, the rank order of existing preferences does not change). Second, to use optimality modeling, economists assume that more is better i.e. an individual behaves as if they are striving to maximise their utility. Finally, as an individual's utility cannot be measured directly, economists assume it is revealed through the choices that individuals make. With these assumptions in place, economists define utility functions that describe how an individual's preferences vary with the amount of a commodity, in order to predict what choices a rational individual should make.

1.1.2. Biological rationality

By contrast, in biology, rationality is implied because evolutionary theory predicts that natural selection will result in living things appearing as if designed to maximise their inclusive fitness. Natural selection is an optimising process; over many generations, it acts to increase the frequency of individuals with genes (strictly, alleles, namely variants of a gene) that confer above-average inclusive fitness, and decrease the frequency of those with below-average inclusive fitness. The end result is a world where living things appear designed to maximise their inclusive fitness[4]. Inclusive fitness measures how an individual's actions affect both their own reproduction and the reproductive success of relatives who share their genes[5,6]. In contrast with utility, inclusive fitness is definable and in principle measurable at the genetic level, independently of the subject's choices.

1.1.3. Optimality models and the study of animal behaviour

As natural selection is an optimizing process, behavioural ecologists commonly use the economic tools of optimisation theory and game theory, which assume organisms behave as fitness-maximizing agents[7]. However, when behavioural ecologists use optimisation theory and game theory, their aim is not to test whether or not animals behave optimally (people know they do not). Instead, they use optimality models as tools to make testable predictions that can help them understand why animals show the adaptations they do[8].

In optimality models, proxies of fitness, such as the number of offspring, number of mates, longevity, food intake, body size, or antler length, are typically used, because it is very hard to measure fitness itself. Better proxies (i.e. those more closely correlated with inclusive fitness) are expected to result in a better fit between the model's prediction and the observed behaviours[9]. Such models have been used with great success in diverse areas of behavioural ecology, including life history studies, sex ratio theory, social evolution theory and foraging behaviour[7].

Note that, contrary to a prevalent misconception in the social sciences, the result that organisms appear as if designed to maximise their inclusive fitness holds whatever the model used to study their evolution i.e. natural selection maximises inclusive fitness, and this is true regardless of whether it is studied using multi-level selection, group selection, graphs, game theory, inclusive fitness, neighbour-modulated fitness or population-genetic based models[10].

1.1.4. Biologists do not expect B-rational behaviour all the time.

Despite the centrality of optimality-based models in behavioural ecology, behavioural ecologists do not expect animals to behave B-rationally all the time[8]. First, as natural selection maximises inclusive fitness over an individual's lifetime, if a behaviour is examined for only a short period, or if it is one that has little bearing on fitness, it may appear maladaptive (i.e. not B-rational)[11]. Second, like humans, animals rely on an array of heuristics when making decisions. Such 'rule-of-thumb' adaptations are widespread as they allow organisms to make fast, accurate choices, with limited information[7]. However they mean that animals do not fine-tune their behaviour to every situation. Third, natural selection acts upon the average consequences of a particular trait. A trait may entail some costs, but as long as the cost:benefit analysis is favourable (i.e. on average it increases inclusive fitness over an individual's lifetime, or even over a number of generations), the trait can be favoured. Thus if a few individuals in a population fail to maximise their fitness, it does not automatically imply that they are not B-rational; natural selection will minimise the average cost of errors, but we do not expect it to eliminate them[12]. Fourth, even behaviourally flexible organisms can only be expected to respond optimally within the range of natural variation they or their species have encountered before. Therefore in unfamiliar environments (such as a laboratory) organisms will fail to maximise their inclusive fitness[13].

More generally, in natural populations, in addition to genes, many other factors influence an organism's chances of survival and reproduction (i.e. its fitness). Stochastic effects (e.g. unpredictable weather), mutation and population movements all change gene frequencies over time, so these are evolutionary forces too. As these non-selective evolutionary forces do not maximise anything, they increase the phenotypic variation, which increases the variation in fitness in the population. Natural selection acts on this increased variation, meaning that over evolutionary time, organisms are subject to a continuous process of adaptation. For all these reasons, there is no expectation in biology, as there is in economics, that organisms should always be optimally adjusted to their present circumstances[11].

1.2. Risk Studies in Biology

The literature on so-called optimal foraging theory is particularly relevant to the study of risk. Classical optimal foraging theory (OFT), assumes that ideal predators maximise their rate of energy gain. Rate of energy gain is described by the function $E/(h+s)$, where E is the amount of energy gained from a prey item, s is the search time involved in finding a new prey item and h is the handling time, which includes catching, killing, eating and digesting the prey[14]. Basic optimal foraging models assume that foragers live in a homogeneous habitat with stochastic, but stable properties. However, to study risk sensitivity, it is inadequate to only measure the average values of variables. Here we review empirical evidence of risk sensitive behaviour in nature (1) and then introduce theoretical work on risk sensitivity (2).

1.2.1. Risk sensitive behaviour in nature

In behavioural ecology, studies on insects, fish, birds and mammals show that risk sensitivity is widespread. For example, if bumblebees are presented with two artificial flowers, that give the same expected average amount of nectar, but one gives a constant amount, while the other a variable amount, they strongly prefer the constant flower; in other words they are risk averse[15]. By contrast, when pigeons are provided with water with either a fixed or variable delay, they prefer the variable option; in other words they are risk prone[16]. When given a similar choice, the preferences of Yellow-eyed juncos have been reported to depend on the ambient temperature: a 1°C they preferred the variable food option, at 19°C, they preferred the constant option[17]. These examples illustrate that there is natural variation in risk preferences, from risk aversion to risk proneness; the theory on risk sensitivity has sought to explain this[18].

Most risk research is based on lab, rather than field studies. There are a variety of experimental set-ups that have been used to study risk. Studies on bees, seed-eating and nectivorous birds typically allow the animal to forage on an array of artificial flowers or dishes, generally identified by coloured markers[15,19,20,21,22]. Preferences are measured by counting the number of visits to each food source. As the reward distributions of each colour type can be varied, this set up allows for precise experimental control over the animal's experience, while mimicking the natural foraging environment[23]. Titration is another option, where preferences between foraging options are explored ether by keeping the options' parameters stable and measuring the degree of preference between them, or by varying parameters until the subjects show indifference[24,25]. Some experimenters use operant techniques: birds can be trained to peck or hop on perches for rewards and mammals may be trained to press levers[26,25]. One difficulty when designing such experiments is to ensure that rate of intake experienced by the subject follow what is intended. Even if the experimental design intends to make rates in the alternatives equal, problems arise if, by chance, the animal experiences above or below average samples of the variable option, or the time it takes to consume different sized food reserves is not taken into account[23].

1.2.2. Risk sensitivity theory

To study risk sensitivity, optimal foraging theory was extended by assuming that there is a potentially non-linear relationship between rate of gain and fitness (thus further approximating the theoretical maximand). Simple mathematics implies that if this relationship is non-linear, then it is adaptive for animals to be risk sensitive[27,28]. To understand why, consider a choice between a fixed option (*A*) and an uncertain option (*B*) that yields outcomes from a stochastic set with the same mean as the fixed value (i.e. $\bar{B}=A$). If the relationship between the energy gain (*x*-axis) and fitness (*y*-axis) is non-linear then even though the average energy gain of the two options is the same, the average fitness gained is not. More formally, for a non-linear function, the expectation of an average does not equal the average of expectations: $f[\text{mean}(x)] \neq \text{mean}\,[f(x)]$. This is known as Jensen's inequality (see figure 1). When the function is concave, fitness is maximised by risk aversion and when the function is convex, $f[\text{mean}(x)] < \text{mean}\,[f(x)]$ and hence fitness is maximised by risk proneness. Thus, a subject that consistently maximises average fitness expectations can (B-rationally) fail to maximise average energy gain or another dimension of their payoff. Risk sensitivity theory (RST) is mathematically equivalent to expected utility theory (EUT); the difference is that RST assumes B-rationality (i.e fitness maximisation), while EUT assumes E-rationality (i.e. utility maximisation).

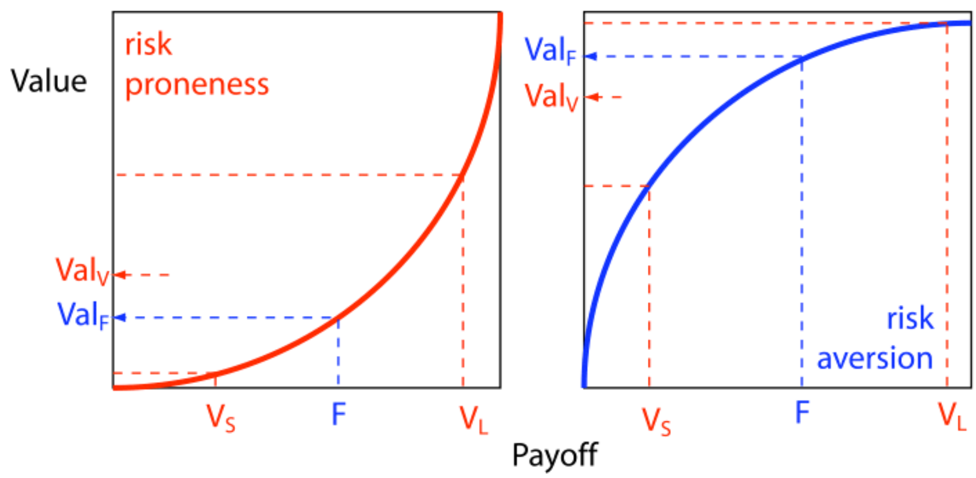

Figure 1. Why non-linear fitness predicts risk sensitivity. The x-axis represents the payoff an individual receives such as the energetic value of food item (or commodity value for EUT). The y-axis represents the value of that item in terms of expected fitness (or expected utility for EUT). Consider two options, a fixed option F, and a variable option, V, with lower and upper payoffs at V_S and V_L, which has a mean value equal to the fixed option F. If the fitness function (or utility function) is non-linear, the expected fitness for the mean of the variable option (Val_V) is not equal the expected fitness of the fixed option (Val_F) i.e. $f[\text{mean}(x)] \neq \text{mean}\,[f(x)]$. Concave fitness functions lead to risk aversion and convex fitness functions lead to risk proneness. This is known as Jensen's inequality. Figure provided by Alex Kacelnik.

Risk sensitivity theory was used to formulate the well-known 'energy budget rule'[29]. The energy budget rule implements the previous result, but assumes the fitness vs resource function becomes a step function between 0 and 1. As both sides of the step are flat, at the point where the fixed and the variable options offer the same expected mean fitness, the RST model predicts a discrete switch from complete risk aversion (preference for the fixed option) to complete risk proneness (preference for the variable option). This discrete switch has a biological rationale. One scenario that illustrates the relevance of the energy budget rule is the question of what energy reserves a small diurnal animal will need to survive fasting through the night, when energy continues to be consumed but is not gained. In some such species, such as hummingbirds, metabolism is so active that they could starve to death if they go to sleep with low reserves. According to the energy budget rule, if the expected fitness gains from the fixed option are sufficient to survive (i.e. exceed the minimum energy reserve threshold), then by choosing it the animal's expected fitness will be 1, and it will be risk averse as there is no possible gain from choosing a risky alternative with the same mean. However, if the fixed option is below the minimum energy reserve threshold, choosing it leads to certain death, while the risky option offers at least some hope, so the animal benefits by being risk prone. Thus evolutionary biologists view fitness maximisation (and hence biologically rational behaviour) as compatible with both risk proneness and risk aversion, depending on the function relating resource gains to fitness consequences. All of this is of course identical when dealing with the shape of utility functions in human decision making.

Unfortunately, despite many experimental studies, there is limited evidence to support the theoretical predictions of the energy budget rule[29]. Specifically, there is limited evidence supporting the model's core prediction, that changes in an animal's energy budget affect risk sensitivity (i.e. that starvation encourages risk proneness and satiation encourages risk aversion)[30]. What empirical studies do reveal however, is that across species there is a robust trend that animals are risk averse in relation to reward amount and risk prone for reward delay (figure 2). Studies which compared responses to both variability in amount and delay have found this pattern, supporting this general trend[26,31,1,25].

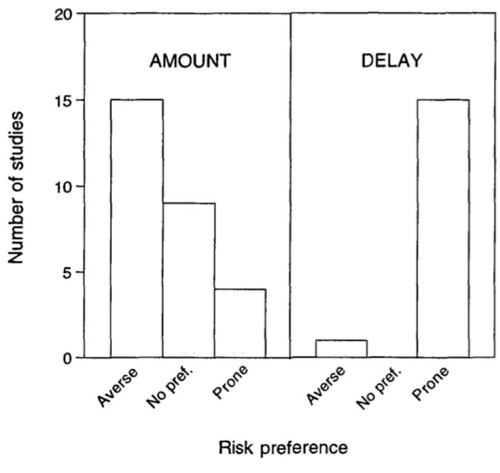

Figure 2. Risk sensitive preferences are different if the variability relates to amount vs delay in food. Risk prone behaviour is found when there is variability in the delay between feedings, and that, although results are more mixed, risk aversion is found when there is variability in the amount of food. Taken from Kacelnik & Bateson, 1996[23].

Given these empirical results, numerous theoretical extensions have sought to understand how risk preferences are affected by an animal's state and why they should differ when variability in the amount vs delay in food (reviewed by Kacelnik & Bateson, 1997[32]). At least one theoretical account argues that the unifying principle is that a quasi-universal mechanism of information processing exists which causes biological agents to be risk averse towards dimensions they are designed to maximise and risk prone towards those they strive to minimise[26,33]. This account is, to the author's knowledge, the only attempt to provide a single explanation to human phenomena such as the contrast between risk aversion for gains and risk proneness for losses and non-human expressions of risk sensitivity in the biological realm.

This increasingly influential explanation is provided by Scalar Utility Theory (SUT), a mechanistic theory that considers how the accuracy by which animals process and remember information affects their risk preferences[23,33]. SUT builds upon Weber's law, which states that the difference in the magnitude of two stimuli necessary for an animal to notice that they are different is proportional to the mean value of the stimuli. Thus following Weber's law, the accuracy with which an animal will perceive, remember and recall the value of a given stimulus will fall within the range of its true value plus or minus this just-noticeable difference (JND). An animal that encounters the same item repeatedly (a fixed source) would create a mental representation of how it remembers the item's value that would approximate to a normal distribution, with the true value of the stimulus as the mean, and standard deviation proportional to the true value. If instead, the animal encountered variable options, as the animal's mental representation of the mean value of these variable options will be skewed to the right, its mental representation will have a mean value below the true mean value, as the absolute error is greater in higher value items. Therefore as the animal builds up these representations it will judge the variable option as having a lower mean than the fixed option, which makes it preferable for maximised dimensions (food, gains) and the opposite for minimised dimensions (losses, delay to food, pain). Assuming equal long-term food intake rates, the model predicts that an option offering variability in delay should be chosen more often than a fixed alternative and a source offering variability in amount should be chosen less often than a fixed alternative. Thus, if animals do process information according to Weber's Law, SUT offers an explanation for why animals are risk prone when variability is in delay and risk averse when variability is in amount of food.

Another body of theoretical work of particular note has been developed by McNamara and Houston and uses a variety of state-dependent dynamic models to predict optimal behaviour under more complex scenarios[34,35,6,36]. For instance, they take into account the idea that optimal decision makers should consider that choices not only have immediate outcomes but also alter the potential choices to be made later on. In their models, animals decide whether to adopt a risk prone or risk averse behaviour at each time step. In many of their models, the animal's energy reserves change through time as a joint consequence of its choices and the (stochastic) outcomes. This framework shows that risk sensitivity to variability in amount of energy gained is logically distinct from risk sensitivity to variability in the time that each choice compromises (i.e. the time lost from pursuing other options), mainly because the latter affects the number of future choices left in the game.

Some extensions of McNamara and Houston's state-dependent biological analyses are of particular relevance to humans. When risk models incorporate learning they show that, because it is difficult to learn about highly variable food sources, risk-averse behaviour is favoured in a wider range of conditions than risk-prone behaviour. If the environment in which the animals learn is changing, this makes it less likely for risk-prone behaviours to be adaptive[37]. Therefore, risk-aversion may be adaptive even when the optimisation criterion is maximisation of mean long-term rate of food gain. This result may provide an evolutionary explanation for the result that humans are risk averse when they are required to make decisions based on ambiguous, incomplete information[8,38]. Other extensions of RST using state-dependent models show that an animal's expected future reproductive success depends on: (i) the energy reserves of the animal and time of day; (ii) the future foraging environment, specifically the quality of food, whether foraging must cease at a fixed time (e.g. dusk), (iii) whether foraging is likely to be interrupted; and (iv) the biological purpose of the energy, whether it is to be used to avoid starvation, be put into reproduction, or into growth (for a review see McNamara and Houston 1992[18]).

1.3. Proximate determinants of risky behaviour in humans

A vast range of scientific and medical literatures, including genetics, endocrinology, neuroscience and psychology hold insights that provide proximate explanations for how humans perceive and respond to risk, and what the genetic, hormonal, environmental and social factors are that affect these behaviours. This section considers a small fraction of this literature, and focuses on work that has attracted recent interest from social scientists. The aim is to give a flavor of these disciplines and to critically assess their ability to answer the sort of questions social scientists and policy makers care about.

1.3.1. Genetic Studies

There is a growing enthusiasm for genetic data in social science research. For example, twin studies (where differences in the behaviour of pairs of identical and non-identical twins are compared) show that some variation in political and economic preferences can be statistically accounted for by genetic factors, including 20% of the variation in risk taking in experimental lotteries [39]. Twin studies measure heritability (the proportion of variance in a trait attributable to genetic factors), but they cannot establish which specific genes are implicated. To do this a second branch of research has emerged which focuses on the effect that specific "candidate" genes have on behaviour. Candidate genes are typically identified via animal studies which artificially knock-out genes to see what happens to an animal's behaviour. Alternatively, they may be identified by simply picking at random huge numbers of genes and testing people for a dose effect, namely if having 0, 1 or 2 representatives of an allele in the genome correlates with some experimental result.

One candidate gene, that was identified from mouse studies and is widely studied in human behavioural research, is the MAOA gene. This gene codes for an enzyme MAO-A (monoamine oxidase-A) that deaminates (breaks down) neuroactive substances such as serotonin and dopamine in the blood. A mutant version of this gene that produces less of the enzyme (the so-called low-activity MAOA gene) is correlated with changes in aggression and impulsivity in mice. In humans, different variants of this gene have been shown to correlate with behavioural variation, including the probability of having credit card debt[40], susceptibility to pathological gambling[41] and a tendency to make riskier financial choices[42].

However, the appropriateness of using candidate gene studies in the social sciences is questionable. An implicit assumption underlying the majority of these studies is that there exist genetic variants whose effects are large enough that they can be reliably detected in samples of the size used (usually several hundred individuals, and no study has used more than 3000[13,43]). To examine whether this approach is appropriate, a recent study compared a twin-study approach and a candidate gene approach to estimate the degree to which specific genes predict their economic and political preferences[44]. From a detailed set of questions, the authors measured twins' political and economic preferences, and found that the twin-based narrow heritability estimates for these traits (i.e. the proportion of variance that is due to genetic factors) were 30%-40%. They then estimated what proportion of the variation in these preferences could be estimated using a variety of candidate genes (common single nucleotide polymorphisms (SNP)). They found that these molecular-genetic-based estimates of heritability did partially corroborate the twin-based estimates, suggesting that molecular genetic data could be predictive of preferences if the causal variants were known. However, the estimated fraction of total phenotypic variation that could, in principle, be explained by all the candidate genes combined was only about one-half of that achieved from twin studies.

The problem is therefore that for an individual gene study, the true effect size is tiny. To measure such tiny effect sizes accurately, sample sizes of many thousands of individuals would be needed[45]. Otherwise, if the sample size is too small relative to the effect size being measured, there is an increased chance that the data will produce false-positive results. Unfortunately, at present most published studies that claim to have found associations between specific genes and economic and political traits have used sample sizes of only a few hundred, which raises serious doubts about the statistical significance of their results[45]. Even if sufficiently large sample sizes were used, and results for the heritability are genuinely significant, the value of such studies for social scientists seems questionable as the proportion of variance explained by a candidate gene, (i.e. the impact the gene has on the trait of interest) is so small. This is because in reality, most behaviours are not influenced by single genes with large effects but by many genes, each of which have a small effect. Therefore while such results may be interesting to geneticists and evolutionary psychologists, they are of little value to social scientists as other factors – sociological, economic and environmental – have vastly more predictive power.

1.3.2. Neurological studies

In recent years, magnetic resonance imaging has been increasingly used to establish correlations between activity in regions of the brain and decision-making involving risk, trust, and other categories of interest. This work has yielded insights of general importance to decision theory. For example, subjective expected utility theory predicts that the probabilities of outcomes should influence choices, whereas confidence about those probabilities should not[38]. However, this assumption has been questioned by neuroimaging studies because they show that different parts of the brain are activated when subjects are faced with ambiguous versus risky decisions. This pattern of brain activation suggests that a person's confidence about the probabilities does affect their choice. In these studies, 'ambiguous' is defined as choices for which probabilities are based upon incomplete information, such as the chance of a lightening strike, and 'risky' as choices where the probabilities of different outcomes are known, such as when gambling on a roulette wheel.

These studies find that making risky choices induced greater activation of the brain's rewards centers than making ambiguous choices[46]. The results suggest that when faced with choices under uncertainty, humans anticipate a lower reward than they would expect from a risky choice[38]. Interestingly, it has been shown that adolescents, who typically engage in more reckless, risky behaviour, have a greater tolerance for ambiguous conditions than older people[47]. These studies suggest that an increase tolerance to ambiguity in youth may make sense, if it makes it easier for adolescents to learn and engage with a still-unfamiliar world.

Magnetic resonance imaging studies have also been used to highlight the role of emotions in risk processing. For example, risk judgments change when individuals perceive fear or anger differently; people disposed to be fearful are more likely to make pessimistic assessments of future events, considering the future unpredictable and incomprehensible, while people disposed to be angry are more likely to make optimistic assessments about the future, which they view as predictable and comprehensible[48]. More generally, a meta-analysis of brain imaging studies, to review what regions of the brain are involved in different risk-related choices, concluded that activation of many brain regions are higher if risky choices involved potential losses (rather than potential gains)[49]. This study supports the increasingly held view that brain regions used for risk processing, especially when there is ambiguity involved, are mostly associated with aversive emotions, such as fear, sadness, disgust and regret[20,50]. Reward centres in the brain are activated when there is no ambiguity; they appear to help the subject value the choice options, when only potential gains are likely[51]. These studies suggest that risky-choices are, at a neural level, dominated by the negative emotions associated with potential losses. They imply that to make risky choices that involve potential losses, or decisions when there is ambiguity, the decision-maker must overcome a hurdle of negative emotions that deter us from taking such risks.

1.3.3. Hormonal studies

Risky behaviour is also being understood from hormonal studies. For example, across species, studies show that testosterone has an important influence on male behaviour. The effects of testosterone includes increased assertiveness and aggression, and a willingness to take risks. Evolutionarily this originates from the fact that male reproductive success is more variable than that of females, due to asymmetric investment between the sexes in individual offspring. As a consequence, males stand to gain more from the relatively unlimited payoff of the upside of taking the risks associated with competition. Concerning risk in men, salivary testosterone correlates with risk-taking in an investment game[52]. City of London traders with higher testosterone have higher long-term profitability, suggesting that financial markets reward risk taking[53].

The work on traders and hormones has led to the suggestion that the irrational exuberance and pessimism observed during market bubbles and crashes may be mediated by steroid hormones[54]. If male hormonal swings can exaggerate market moves, then it implies that the age and sex composition of traders and asset managers may affect the level of instability witnessed in the financial markets[55]. However, caution is needed to not over interpret these findings; several other studies have found no links between testosterone and competitiveness[56,57], and no study to date has established a causal relationship between testosterone and financial behaviour.

A possible explanation for testosterone fluctuations, which was developed by biologists to study bird breeding, is the ‘challenge hypothesis’[58]. This proposes that testosterone promotes male aggression and assertiveness in conditions when it would be beneficial for reproduction. In humans, one of the theory’s predictions is that challenges involving young males competing would raise testosterone. Hence, this may explain the patterns of testosterone in the high-pressure environment of the trading floor[59]. If high levels of testosterone lead to undesirable, risky behaviours, this theory suggests that the remedy will be to alter the age balance and competitiveness of the atmosphere.

SECTION 2: SOCIAL SCIENCES

In the biological sciences, there is a universally accepted theoretical framework (evolutionary theory) that underpins all areas of study. By contrast in the social sciences, while rational choice theory is the dominant framework, it is by no means the only one. This coexistence of theoretical frameworks has generated parallel literatures based upon different, sometimes conflicting, assumptions about the way humans behave or societies operate. Furthermore, the classification of models into normative, mechanistic or descriptive is not always as straightforward as it is in the biological sciences. The aim of this section is to introduce both the theoretical models that are used to study risk in humans, and the diversity of empirical studies that help build a picture of how humans respond to risky choices. The first part of this section introduces the mainstream economic theories of risk. Part 2 reviews some of the empirical evidence that challenges the assumptions of this economic theory and part three discusses a variety of models that illustrate some of the alternative ways economists are modeling risk: prospect theory, regret theory and non-ergodic models. The fourth part, turns to the sociological and anthropological literatures, and introduces the psychometric paradigm and cultural risk theory.

2.1. The standard economic model of risk

This part introduces the most widely used economic model of risk, which is expected utility theory and briefly illustrates how its more complex extensions are used to model investments.

2.1.1. Expected Utility Theory.

In many situations, individuals face risky decisions, where they cannot be certain about the utility of the options available to them. Expected utility theory (EUT), developed by John von Neumann and Oscar Morgenstern, is used to model cases where the probabilities of different outcomes are known. As mentioned above, Risk Sensitivity Theory and Expected Utility Theory are mathematically equivalent. Nevertheless, it is valuable to briefly describe the model again, but this time, in terms of E-rationality.

Economists describe the outcomes of a risky choice as a lottery, where the elements of the lottery correspond to the probability that an outcome will arise in a given state of nature. In addition to the standard assumptions of rational choice (complete, transitive, independent preferences), EUT assumes continuity, which is that if there are three lotteries (A, B and C) and an individual prefers lottery A to B and B to C, then there is a combination of A and C where the individual is then indifferent between this mix and lottery B. To calculate the expected utility of a lottery, the utility values of each possible outcome, multiplied by their respective probabilities, are added together. Thus, when faced with a variety of risky choices to choose from, the theory assumes an individual makes a choice by comparing the expected utility values of the different lotteries. In other words, in expected utility theory, an individual's set of preferences is between lotteries, not fixed outcomes.

Often, instead of comparing two risky choices, models consider when a risky outcome is preferred over a certain one that has the same expected value. In other words, they consider when the expected utility of a lottery will be higher than the utility of a fixed choice. If the mean of a risky choice equals a fixed choice, then if an individual is risk-insensitive, they are indifferent between the two options. However, if the individual prefers one of these options then they are risk sensitive. In general, people are risk sensitive: for example if asked "would you prefer £500 or a 50% chance of winning £1000", most people choose the £500. In other words, although the means of both options are the same (£500), the utilities are not, because the expected utility function is concave, meaning the utility of the fixed option is higher than the utility of the variable option. Conversely, if a person prefers the gamble, they are risk prone and then their expected utility function is convex. As with Risk Sensitivity Theory, this result is expressed by Jensen's inequality (figure 1), which states that when the utility function, f(*x*), is a non linear function of *x* (the above example assumes that the commodity in question is money; x=£), then $E[f(x)] \neq f(E[x])$. Thus the direction of Jensen's inequality describes whether an individual will be risk averse, or risk seeking and the stronger the curvature of the utility function, the stronger the risk sensitivity and the larger the 'risk premium', which is the difference in terms of *x* between the expected value and the certainty equivalent.

2.1.2. Investment models.

Models of investment, asset prices and the cost of business cycles depend on the assumptions about the relationship between risk preferences and wealth. Therefore, an important issue for economic modelers is how risk preferences change with wealth. However, the model just described assumes expected utility is unchanged by affine transformations (changes to the scale on the *x* axis). This assumption is challenged by empirical evidence which shows that people tend to be risk averse (i.e. they have a concave utility function), and that their degree of risk aversion changes with wealth. Therefore, to incorporate this possibility that risk preferences depends on wealth, Kenneth Arrow and John Platt developed an alternative measure of utility, which stays constant even when the scale changes. This is known as the coefficient of absolute risk aversion[60], and is defined as:

$$A(x) = -\frac{u''(x)}{u'(x)}$$

If $A(x)$ is decreasing/increasing, then an individual will show decreasing/increasing absolute risk-aversion (DARA/IARA). If changes in wealth do not affect an individual's risk aversion, they show constant absolute risk aversion (CARA). Models that assume DARA are popular in financial risk management as empirical evidence on investor behaviour is consistent with DARA[61]. For this reason, it is often assumed that wealth levels are a proxy for risk aversion.

However, for many financial questions, absolute risk aversion is not an ideal measure for comparison. For example, if an individual were willing to gamble 10% of their wealth with a 50-50 probability of doubling or losing it when they are poor, would they still take this gamble if they were rich? Questions such as this, which concern relative, not absolute wealth, can be understood by redefining utility in terms of relative risk aversion, which Arrow-Platt defined as:

$$R(x) = xA(x) = -\frac{xu''(x)}{u'(x)}$$

Like for absolute risk aversion, the corresponding terms constant relative risk aversion (CRRA) and decreasing/increasing relative risk aversion (DRRA / IRRA) are used. If someone exhibits DRRA, the answer to the question just posed is yes. This benefit of the relative measure is that it is still a valid measure of risk sensitivity, even if the utility function changes from risk-averse to risk-seeking as x varies, i.e. utility is not strictly convex/concave over all x.

Asset managers use these concepts of relative and absolute risk aversion to build investment portfolios for their clients, which combine risk-free and risky assets. They typically assume that if a client experiences an increase in wealth, he/she will choose to decrease the investments in risky assets held in the portfolio if absolute risk aversion is increasing.

2.2 Empirical challenges to standard economic assumptions

In economics, rational choice begins by characterizing an individual's preferences and the constraints that individuals face when making choices. Preferences are assumed to be exogenous and stable with regard to the changes in the constraints, thus behavioural changes are explained as optimal responses to changes in the payoffs and the available set of actions. For this reason, economics has traditionally viewed preferences as stable across cultures and invariant across experimental contexts[62]. As preferences reflect an individual's self interest, standard models of rational choice assume that an individual's utility is unaffected by the payoffs others receive. These standard models also assume that decisions reflect the core assumptions of rational choice – namely completeness, transitivity and independence of preferences. This part discusses some of the numerous studies that investigate how human behaviour deviates from the predictions of rational choice. It introduces the 'cognitive biases' literature (1), visits the social preferences literature, which shows that people do not always act in their narrow self-interest as they care about the welfare of others (2) and finally discusses the fact that between cultures, there is substantial variation in attitudes towards risk (3).

2.2.1. Cognitive biases

Economic and psychological experiments reveal that human behaviour systematically violates the expectations of rational choice models in predictable ways. These predictable deviations are described as 'cognitive biases'. This part illustrates this vast literature by briefly describing seven wellcharacterised biases that are relevant for studies of risk. An interested reader is invited to visit the references associated with the list of over eighty cognitive biases given on Wikipedia*.

2.2.1.1 Framing
Framing effects occur if the way information is presented to a reader leads to systematic shifts in their preferences[26,31,63,64]. For example, people evaluate the risk of medical treatments differently depending on whether attention is drawn to the chances of dying or surviving[65]. One might think that as financial decision-making is an area where the use of rational calculation is particularly encouraged, framing would have less effect. This is not so. For example, when trained financial professionals were asked to estimate the value of a company's stock based on its annual report, they judged the companies with aesthetically pleasing reports to be 20% more valuable, despite the fact all reports contained identical financial data[66].

2.2.1.2 Availability bias
Availability biases reflect the fact that people tend to judge the probability of a hazard occurring by the ease with which examples of it come to mind, rather than by relying on objective estimates. People know in general terms which hazards cause large numbers of deaths and which cause few deaths, however because relatively they hear about unusual deaths more often than common ones, people severely overestimate the frequency of rare causes of death, and severely underestimate the frequency of common causes of death[67]. Similarly, people underreact to threats they cannot imagine, which is why people who have never experienced floods, rarely buy flood insurance, even when it is heavily subsidized.

2.2.1.3 The affect bias
The affect bias refers to the tendency people have to form an overall impression on the basis of partial information, and then allow this impression to influence future judgments[68,69]. For example, Finucane asked people for their views about the safety and benefits of nuclear power and showed that providing information that increased perception of the risk, decreased perception of benefit, and providing information that decreased perception of benefit, increased perception of risk[70]. This same effect has been demonstrated in the realm of finance. When analysts were asked to judge risk and return for unfamiliar stocks, they relied upon a general affective attitude. Stocks perceived as "good" were judged to have low risks and high return; stocks perceived as "bad" were judged to have low return and high risks[71]. Ganzach found that the affect heuristic was relied upon more heavily when the analyst had less information about the asset[71].

2.2.1.4 Overconfidence
People place excessive confidence in the accuracy of their estimates. For example, imagine you were asked to guess an uncertain quantity, such as the total bonuses that were paid to bankers in the City of London in 2010. Instead of a precise number, you were asked for an upper and lower value such that you are 98% confident that the true value lies within it. If you are accurate,

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* http://en.wikipedia.org/wiki/List_of_cognitive_biases

then in a test with one hundred such questions, on average only 2 of your answers should be outside the value ranges you gave. However, when Alpert and Raiffa asked subjects 1000 general-knowledge questions like this, 42.6% of the true values lay outside the subjects 98% confidence intervals. When subjects was asked to estimate 99.9% confidence upper and lower bounds, the 0.01% happened 40% of the time.

2.2.1.5 Hindsight bias

Hindsight bias describes the fact that after learning about an outcome, people give a much higher estimate for its predictability compared to people who must predict the outcome without advance knowledge. This bias has important implications in both legal and financial settings. In legal settings, a judge or jury are often required to decide whether by failing to foresee a particular risk, a defendant was legally negligent or not[72]. In an experiment based on a real case, participants were asked to estimate the risk of flood damage caused by a blocked bridge, and hence whether the bridge owners were negligent. One group were given the same information known to the city when it decided not to watch the bridge, and another group was given this information and told about the flood that occurred. Only 24% of the first group found the owners were negligent, compared to 56% of the second group. Interestingly, a third group was told about the flood and explicitly informed about hindsight biases and asked to avoid it. However this made no difference: 56% of this third group also concluded the city was legally negligent[73].

Taleb suggests that a combination of overconfidence, hindsight bias and availability bias explain why banks fail to guard against Black Swan events (major, surprise events)[74]. He gives the example of a trader whose strategy worked for six years without a single bad quarter, yielding close to $80 million, before he lost $300 million in a single catastrophe. If traders mistakenly believe that the past was predictable, they will also conclude that the future is predictable, so will fail to understand the risks they are taking[75].

2.2.1.6 Anchoring

Anchoring occurs when people's decisions are influenced by arbitrary reference points ("anchors")[76]. For example, two groups of students were asked whether Mahatma Gandhi died before or after age 9, or before or after age 140. Then they were asked to estimate what age he died at. Both anchors are obviously wrong, yet the two groups guessed significantly different average ages (50 vs. 67)[77]. Such effects remain even with financial incentives and explicit instructions about the problem of anchoring[78].

2.2.1.7 Bystander effect

The bystander effect is the label given to the fact that when individuals are part of a group, this reduces their sense of responsibility. In a famous series of experiments, Latanée and Darley described the bystander effect where larger numbers of people are less likely to respond in emergencies[79]. They found that 75% of subjects alone in a room, noticing smoke entering from under a door, left to report it. By contrast, when three naive subjects were present, the smoke was reported only 38% of the time and when a naive subject was in the presence of two confederates who purposely ignored the smoke, the left to report the smoke only 10% of the time.

This effect is usually explained as resulting from a sense that responsibility is diffused. Everyone hopes that someone else will handle the problem instead, and this reduces the individual pressure to the point that no one does anything. Caildini explains: “Very often an emergency is not obviously an emergency. In times of such uncertainty, the natural tendency is to look around at the actions of others for clues. We can learn from the way the other witnesses are reacting whether the event is or is not an emergency. What is easy to forget, though, is that everybody else observing the event is likely to be looking for social evidence, too. Because we all prefer to appear poised and unflustered among others, we are likely to search for that evidence placidly, with brief, camouflaged glances at those around us” (p.114, Caildini 2009). Everyone sees everyone else looking unconcerned and failing to act, so nothing is done to put out the fire[80].

2.2.2 Pro-social preferences

Another significant finding, which challenges a core assumption of rational choice models is that people cooperate at levels higher than predicted if they were simply maximizing financial gain, even in anonymous one-shot economic games[81-83]. For example, in public-goods games, which are used to model collective-action problems, individuals can produce benefits that are shared by all members of their group, including themselves. In the standard set up, individuals wishing to maximise their own incomes should contribute nothing, yet individuals do contribute something, even in one-shot encounters (typically 40-50%). If play is repeated, investments decline, but levels of cooperation remain significant (typically around 10-20%). It is argued that these results show people value the welfare of others in a way that is perhaps unique in the animal world[81-83]. Individual-level data shows there is stable individual variation, with about 50% of the population behaving as if they are conditional cooperators – that is they condition their level of cooperation on the actions of others[84].

These results, together with experiments that examine the role of punishment, have led economists to conclude that people have ‘prosocial preferences’. Furthermore, prosociality is argued to be the product of evolutionary processes that are unique to humans, however this is strongly criticized by evolutionary biologists[10,85]. It is uncontroversial among biologists that humans have complex behavioural adaptations for social living, and would not behave in the self-interested way traditional economic models assume. Nevertheless, biologists are strongly critical of the broader interpretations given to the results of many economic experiments. In addition to theoretical disagreements, recently, biologists have published experimental results which question whether fixed prosocial preferences are the correct explanation for the results of economics games[86-88]. For example, Kummerli and colleagues adjusted the public goods game so that strategies for selfish and prosocial players were aligned at 100% cooperation (by making the payoffs to contributing to the public good far higher, so it became directly profitable). Standard economic models would predict 100% contributions, however contributions instead started at around 50% and gradually increased, but never reached 100%[87]. Following the prevailing logic, this is evidence for anti-social preferences. The authors (who are biologists) suggest that instead, participants may be largely indifferent to the welfare of others and are simply engaged in imperfect payoff-based learning.

These contrasting interpretations of results in such games highlight the importance of distinguishing the function and mechanism of decision-making. As discussed in section 1, biologists have always distinguished between the selective forces that shape behavioural mechanisms and the mechanisms themselves, implying that suboptimal choices are to be expected when current payoffs differ from those prevalent during evolution. Similarly, Gigerenzer and colleagues have argued that individuals can be expected to use heuristics (rules-of-thumb) that are ecologically rational, namely work well for problems prevalent in the environment (see section 2.3.3), but may lead to cognitive biases in unfamiliar settings. By this logic, the anonymous, one-shot interactions of the public good games in which irrational prosocial behaviour is detected, can simply reflect the rarity of one-shot anonymous circumstances for adult humans raised in integrated social contexts.

2.2.3 Cross-cultural variation in risk preferences

Numerous studies show inter-cultural variation in risk perceptions[89], such as cross-cultural differences in the perception of health and safety risks [90-92]. Bontempo, Bottom, and Weber[93] observed cross-cultural differences in the perception of the riskiness of financial gambles, comparing students and security analysts from the USA, the Netherlands, Hong Kong and Taiwan. Hsee and Weber[94] found that Chinese students were significantly less risk averse than Americans in their choices between risky options and sure outcomes, both when outcomes involved gains and when they involved losses. These authors showed that the degree of country collectivism predicted the magnitude of risk perceived by different nationalities to be inherent in risky financial options[92]. They argue the variation in financial risk preferences reflects the fact that individuals living in more collectivist cultures are cushioned from the consequences of negative outcomes, so can get away with more risky decisions[92].

More generally, cross-cultural behavioural economic studies demonstrate that cultural background has a substantial impact on an individual's economic behaviour[95,96]. For example within cultures, fairness beliefs covary with the degree of an individual's market integration, punishment covaries with their community size[97] and an individual's relative socio-economic status affects how willing they are to trust others[98]. (As an aside, this work highlights the problems of over generalizing the results of studies where all participants are 'WEIRD' - from western, educated, industrialised, rich and democratic societies[99]).

2.3 Alternative ways of modelling risk

A core part of any model of risk behaviour are the assumptions made about how consumers evaluate risky choices. The vast majority of models assume that people evaluate gambles according to the expected utility framework, despite the fact that experimental works shows people systematically violate this theory's assumptions. In response to these experimental results, there has been an explosion of descriptive models that aim to better capture the experimental results. These include prospect theory[63,100], regret theory [101,102], disappointment aversion[103] and rank-dependent utility theories[104-106]. This part briefly considers the first two. The second half of this part introduces two completely different theoretical frameworks; adaptive heuristics and non-ergodic models, which both respond to weaknesses in EUT.

2.3.1 Prospect theory

Prospect theory, developed by Kahneman and Tversky, aims to account for the experimental results that show people as loss averse[100]. Loss aversion is a cognitive bias that implies that that if someone loses $100, they will lose more satisfaction than another person would gain in satisfaction from a $100 windfall. Unlike EUT, prospect theory is descriptive (its aim is to reflect how people behave, not predict how they should behave). It assumes that people make decisions in two-stages: editing and evaluation. In the editing phase, it assumes the outcomes of the decision are ordered on the basis of a loss aversion heuristic. In particular, the model assumes that people decide which outcomes they consider to be equally valued, and attach a reference point to those outcomes (figure 3). Having decided on their reference point, people then view lesser outcomes as losses and greater ones as gains.

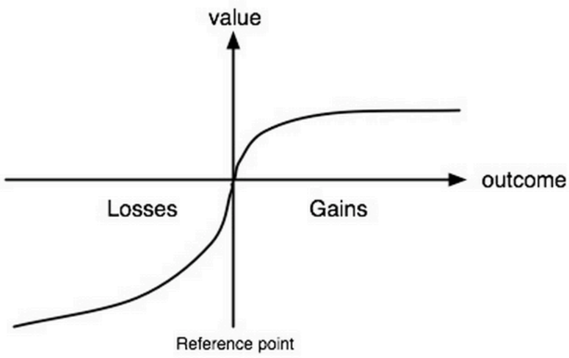

Figure 3. The utility function in prospect theory is altered by the decision-maker's reference point

(image copied from Wikipedia http://en.wikipedia.org/wiki/Prospect_theory)

In the evaluation phase, people are assumed to behave as if they are computing an expected utility value, based on the potential outcomes and their respective probabilities. Thus prospect theory differs from expected utility theory because the utility function is transformed into an s-shape, where losses below a reference point hurt more than gains above it. Therefore small probabilities of big losses are overweighed.

Prospect theory has been successfully used to study a variety of cognitive biases such as the endowment effect (people are more loss averse when making choices about money they've been given, rather than stand to gain) and the reversal between risk aversion and risk seeking behaviour in cases of gains vs losses, which can explain why the same person may choose to buy both insurance and lottery tickets. It has also been used to explain the role of subjective framing effects, which can be understood as causing people to shift their reference point in response to different ways the information is presented.

Prospect theory has been successfully applied to financial contexts (for a review see Edwards 1996[107]). For example, it has been suggested as an explanation for the equity premium puzzle[108]. That is the puzzle that even though stocks on paper appear to be an attractive asset (high average returns), investors are generally unwilling to hold them, hence the premium. Benartzi and Thaler suggest that if people are loss averse with short time horizons, as empirical studies suggest then they would find investments with fluctuating values as unattractive, compared to investments that fluctuate less. This is because they will value the losses in stock value more than the gains[109].

2.3.2. Regret theory

Regret theory, like prospect theory, was motivated by experimental evidence that people behave in ways that systematically violate the axioms of rational choice[101,102]. The model considers utility is a measure of happiness or satisfaction, and therefore argues that in choiceless situations, people can still have a positive utility. They assume that individuals faced with a choice will either regret or rejoice in their choice, based upon the difference between the actual payoff an individual receives and the payoff they would have got had a different course of action been chosen. A negative difference is regretted, while a positive difference is rejoiced. They assume that individuals seek to minimise regret, rather than maximising rejoicing, and use a minimax approach to determine an individual's best course of action. Regret theory is mathematically simpler than prospect theory and contains fewer assumptions. It has been successfully used to explain hedging choices in investment in cases where other models (traditional expected utility, prospect theory or disappointment decision theory) has not[110].

2.3.3 Adaptive heuristics

From a biological perspective, cognitive biases that generate predictable irrationality may reflect the fact that human use heuristics when making decisions[111,112]. Heuristics help people to make rapid, effective decisions based on a limited number of cues. The benefit of heuristics is that they allow people to quickly find good approximate answers. The B-rational perspective assumes that, natural selection will minimize the average cost of any errors that result from making such approximation, but there is no expectation it will completely eliminate them. Therefore heuristics are not expected to lead to perfectly rational behaviour in every situation, and this will be particularly true when individuals are placed in unfamiliar environments which their heuristic rules are not adapted to. In these cases heuristics give rise to systematic errors, which have been called cognitive biases.

A stronger claim made in the heuristics literature is provided by Gerd Gigerenzer, who argues that in the real world, heuristics not only save time, but they can be even more accurate than the best "rational" decisions as defined by logic or statistical models[111,113-115]. For example, a study compared the accuracy of a simple heuristic and a complex model to predict how active that customer will be in the future. The heuristic – has the customer purchased in the past 9 months? – correctly classified 88% of the customers, whereas a state-of-the-art Pareto, negative binomial distribution model, which incorporated parameters for purchasing and dropout rates, correctly classified 75% of customers[116]. Therefore in complex worlds, simple heuristics, which ignore information, can lead to higher predictive accuracy than more complex regressions of algorithms. This is known as the 'less-is-more' effect. This is especially true for low predictability and small samples.

2.3.4. Non-ergodic models of risk

Most economic models, including expected utility theory, assume that expectation averages are the same as time averages i.e. they model risky choices in an ergodic system. An ergodic system is a zero-sum game; time is irrelevant and has no direction, so the system is indifferent to its initial conditions – wherever it starts, it will eventually arrive at the same equilibrium[117]. For example, the outcome of a coin toss is ergodic, because if 1000 people were asked to flip a coin once, or one person was asked to flip a coin 1000 times, the same result would be found from both the ensemble average of the 1000 people, and the time average of the one person (50% heads, 50% tails). By contrast, a non-ergodic system is one where the ensemble and time averages are not the same, so the individual's initial starting conditions and length of time they perform the behaviour matter (figure 4).

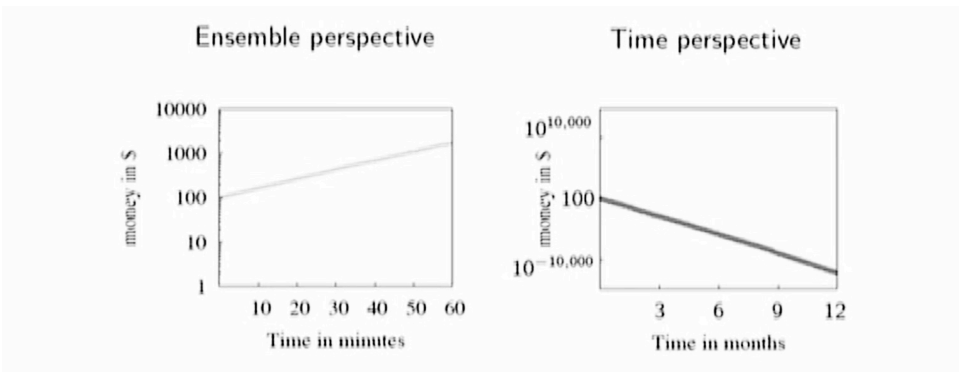

Figure 4. Comparing the expected payoff of a coin toss when heads increases the endowment by 50% and tails decreases it by 40%. (Taken from Ole Peters' TEDx talk 'Time and Chance', Goodenough College, April 2011)

Economists typically assume the system they are modeling is ergodic (where both ensemble and time averages are the same). However, the reality is that the world is non-ergodic and relaxing this assumption can radically alter what the income maximizing strategy is predicted to be. For example, consider an individual choosing between a variable and a fixed option. They are given $100 and can choose either to keep it or can choose to toss a coin, where heads causes their endowment to increase by 50%, and tails causes it to decrease by 40%. Assuming that utility is linear on expected payoff, expected utility theory, which uses ensemble averages, would predict that an individual should be risk prone as the risky choice on average yields the greater income. By contrast, a non-ergodic model, which uses the time average perspective, predicts an individual would maximise their income by being risk-averse and choosing the fixed option. This is because, on average, an individual who repeats this choice many times will lose their money if they make the risky choice as over time, the impact of a 50% gain and a 40% loss is not the same. To see this, imagine you start with $100 and then toss heads and tails sequentially. You will earn $50 (+50%), then lose 40%, and will be $90, then you will earn $45 (+50%) and lose 40%, and be left with $81 and so on, until you have no endowment left to play with.

EUT does not reveal this pattern that, over time, the majority of individuals who make the risky decision will lose everything. EUT's ensemble perspective correctly finds that that if equal numbers of individuals chose both options, the total amount of money earned by those who chose the variable option would be greater than the total earned by those who chose the fixed option. However, EUT does not capture the emerging inequality in payoffs that occurs if individuals make repeated risky choices. Non-ergodic models show that within the risk-prone group, then the proportion of individuals who lose all their money increases through time, and the aggregate benefits are concentrated into an ever-decreasing number of lucky people (who have tossed more heads than tails). In other words, ergodic models of risky choices, such as EUT, greatly overemphasize the benefit of rare exceptions.

Peters' work on non-ergodicity and risk preferences shows that expected utility models are a good approximation for small amounts of wealth, as ensemble-average growth approaches time-average growth as the leverage approaches zero. However, if leverage is higher, Peters shows that expected utility models give inaccurate predictions about the returns an individual can expect from a risky decision as EUT underestimates the cost of fluctuations for individuals. This mismatch is problematic for portfolio construction, which typically uses ergodic models, as it can lead to inappropriate estimates of what risk an investor should take. For example, for an investment where the expected rate of return is greater than the costs of borrowing, EUT would predict the expected rate of return on the investment would continue growing so that the more the individual borrows, the higher their expected return. By contrast, the time-average perspective recognises that because of fluctuations, if an individual makes a risky choice, then eventually by chance they will lose their money. Therefore unlike EUT, the time-average perspective predicts an optimal degree of leverage an individual should maintain in order to optimize their time-average growth rate[117].

2.4. Sociological approaches

Many high-profile controversies, such as concerns about the safety of nuclear power stations, result from a disjunction between public perception and the objective risk assessments made using formal measurements. When experts are asked to assess risk, they expect risk perception to be synonymous with formal measures of risk[118]. However, the public does not perceive risk in the way formal models estimate it. Therefore, risk managers and policy makers need to understand how people perceive and respond to risks, particularly in financial settings where there is often a feedback between the risk perceptions of people and the degree of risk (such as the risk of a run on a bank, or share collapse).

In order to understand how an individual's emotions, beliefs, background and culture explain their individual and collective perceptions, judgments and responses to different risks, sociologists and anthropologists have developed descriptive frameworks that aim to measure the subjective evaluations people make about the probability and impact of different potential hazards. Many social scientists consider risk is a human construct, a subjective measure that helps people understand and cope with the dangers and uncertainties of life [2]. Therefore, in contrast to more quantitative disciplines, such as economics and engineering, that accept that formal models can provide objective measures of risk, many social scientists and anthropologists would argue that risk is not something that can be objectively measured. The rest of this section uses a looser definition of risk, which incorporates both risk (variable outcomes) and uncertainty (lack of information about those outcomes) into the single term. It introduces the two dominant approaches that are used to study subjective risk perceptions: the Psychometric Paradigm and Cultural Risk Theory.

2.4.1 The psychometric paradigm

This psychometric paradigm, pioneered by Paul Slovic, aims to understand what it is about a particular risk that causes a person to over or under estimate its magnitude, relative to the risk's objectively measured consequences[119]. This is a mechanistic approach, derived from experimental data, which assumes that the way a person perceives the probability, uncertainty and potential impact of any given hazard depends on the qualities of that hazard. The psychometric approach reveals that, in line with the affect bias (see section 2.2.1.3), people link risk to pleasure: the greater the pleasure or benefit, the lower the perceived risk and conversely, the greater the dislike or cost, the higher the perceived risk[68,69].

To measure risk perceptions, people are asked to rate a potential hazard for factors such as its controllability, immediacy of effects, and number of deaths it can cause. As the way people score the different qualities of a given hazard are highly correlated, these different qualities are analyzed by principal components analysis and grouped into two summary factors: 'dread risk' and 'unknown risk'. These are then used as axes upon which different hazards can be plotted. Note that this definition of risk concerns subjective perceptions; it does not assume the risk's impact or probability can be estimated. Here, dread risk refers to the perceived lack of control or the catastrophic potential of a hazard. Unknown risk captures the degree to which the hazard is perceived as unfamiliar, new, or delayed in the manifestation of harm. The result is a qualitative representation of risk attitudes and perceptions. Figure 5 (from Slovic, 1987[120]) illustrates this approach, which describes public perceptions of 87 hazards. The higher the perceived risk (i.e. the closer to the upper right corner), the more people want to see risks reduced, and the more they want to see strict regulation.

Social scientists can use this approach to determine the degree to which the risk of any given hazard is subject to social amplification by assessing the mismatch between the objective estimates of a risk's impact and probability and the public's perception of that risk[121]. Social amplification helps explain why, for example, the public are widely supportive standards to control the use of formaldehyde (a hazard that is both dreaded and unknown), which was estimated to cost over £45 billion per life saved[122], but are not clamoring for massive investment in smoking cessation services, despite the fact that the estimated average cost per life saved is just £684[123].

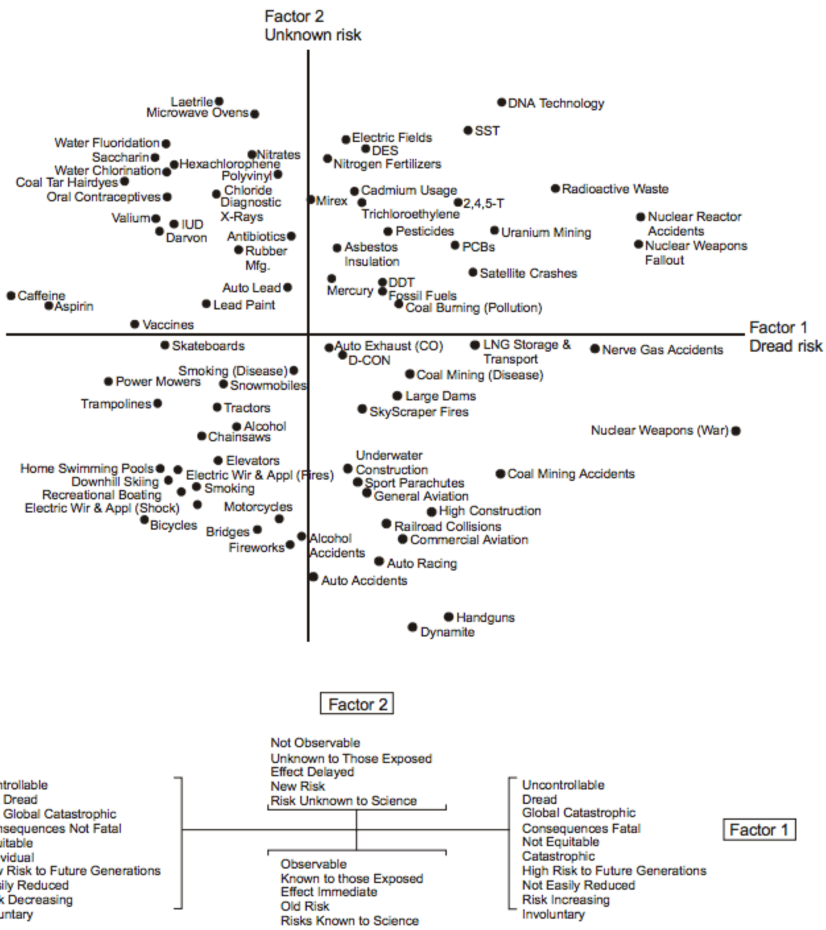

Figure 5. Psychometric measures of perceived risk. People are asked to qualitatively rate 87 hazards for a variety of risk characteristics (listed in the lower diagram). The ratings for these characteristics are combined to produce two composite factors: dread risk and unknown risk. From Slovic 1987[120]. The definition of risk used here is a sociological one, which combines the formal definitions of risk and uncertainty.

2.4.2. Cultural Theory of Risk

Cultural Risk Theory (sometimes known as grid-group theory) was developed by social anthropologists to understand the inter-societal differences in risk perceptions. Cultural theorists argue that the psychometric approach is incomplete because it cannot answer questions such as ‘Why is one technology feared in one society or social context and not in another?’. Cultural theory is a descriptive approach derived from anthropological analyses of differences between societies or groups. It attempts to explain cross-cultural differences in risk perception by arguing that different social structures cause variation in the way people respond to potential societal dangers (hazards)[124].

The theory suggests that individuals reduce their anxiety about hazards they perceive as risky by adhering to social norms. These may or may not in practice effectively mitigate the hazard, but they make the person feel better about it (e.g. to cope with your fear of pollution, you take pains to recycle your rubbish). Cultural theory argues that when individuals adopt such social norms, they will then pressure others to follow them too. Therefore, Douglas argues that our desire to minimize how exposed we feel to the hazards we fear is what motivates us to enforce social norms on those around us. For example, someone who fears the impact of pollution and therefore recycles, may feel stressed when they see people litter, because it reminds them of the dangers of pollution. Therefore, to feel better, they will encourage or coerce people around them to stop littering and start recycling.

Cultural risk theory considers that these micro-level processes of people using norms to cope with what they perceive as risky, and then pressuring others to follow them too, leads to the emergence of social structures at a macro-level, which can be understood in terms of the risks a society views as most serious. These social structures are categorised using two dimensions: “group” and “grid”, where group describes the spectrum from collectivism to individualism and grid describes the spectrum from egalitarianism to hierarchy. The theory also recognizes that there is a feedback between an individual’s perceptions and the social institutions and cultures they live in as an individual’s preferences are, in part, shaped by the culture they belong to. This explains why people from different cultures, living in a shared environment, can have very different risk perceptions. The theory predicts that social change occurs when an individual’s experiences of what risks they should fear no longer fits with the risks the social structure they belong to prioritize[125].

This framework has been used to categorise different organisational cultures within firms and to study ‘cultural surprises’, where sudden shifts in policy or social structures occur because public perceptions change enough to cause a shift from one social type to another[126]. Concerning risk management, cultural theorists have examined why it is so difficult to get banks or firms to adopt uniform risk management standards. They argue the difficulties stem from the fact that a business leader’s risk perceptions depend on the type of organisational structure they work in. Different organisational structures will mean business leaders have different risk perceptions. Therefore, the same standard will be seen by some firms as creating unnecessary restrictions and by others as encouraging excessive risk. Cultural risk theorists argue that current efforts to communicate and educate business leaders about the importance of managing particular risks is futile; the problem is not that business leaders do not understand the risks, it is that they have fundamentally different risk perceptions[127-129].

SECTION 3. RISK, BEHAVIOUR AND REGULATION

The findings from behavioural studies have broad policy and regulatory implications. Policymakers and regulators increasingly realise how important heuristics are in consumer and investor decision-making, how important the effects of systematic cognitive biases such as anchoring, framing and overconfidence are, how levels of financial illiteracy among consumers are far lower than standard models assume and how heavily influenced people are by social information such as reputation, trustworthiness and the prevailing social norms when making decisions. Together, these behavioural insights raise important policy questions. For example, how should the ways people learn and retain knowledge shape communication policy? How should findings about self-control inform policies to prevent over-indebtedness? Can communication strategies help adjust risk perceptions to reflect objective measures of risk? What are the best ways to disclose financial information so that consumers can understand it? Which default options help consumers avoid unnecessary risks?

To facilitate the development of government policy based on behavioural studies, the UK government established the Behavioural Insights Team shortly after the 2010 general election. This followed the publication of the highly influential MINDSPACE report[130,131], which summarised insights from economics and psychology that were considered relevant for policy design. This section gives examples of the policies the Behavioural Insights Team, and other regulators have implemented. Specifically, it discusses work on financial literacy (part 1), 'nudge' based policies (part 2), behavioural-insights inspired information provision (part 3) and education (part 4) and finally suggests some more drastic solutions (part 5).

3.1. Financial literacy

The vast majority of people struggle to process basic statistics such as percentages and probabilities. For example, a recent survey asked US and German adults "which of the following numbers represents the biggest risk of getting a disease? 1 in 100, 1 in 1000, or 1 in 10?". This was answered incorrectly by 25% of US and 28% of German participants[132]. These US results are representative of the levels of financial illiteracy in other countries [133,134].

Understanding the degree of financial literacy is essential for effective regulation. If consumers do not understand the financial choices they are faced with, this suggests they will behave in irrational ways when making financial decisions. This issue is particularly important given that over recent years, there has been a trend towards increasingly complex financial instruments. For example, individuals who don't understand interest compounding may engage in high-cost credit-card borrowing, or they may be more likely to pay high fees when using financial services. This is supported by studies showing that individuals unable to calculate interest rates, borrow more and buy fewer stocks and shares[135]. Financial literacy is also closely tied to retirement planning, saving behaviour and wealth accumulation[136]. Unsurprisingly, financial illiteracy is disproportionately higher in the most vulnerable members of society, as it is correlated with education, gender, race, income, IQ and health[137]. When these demographic variables are controlled for, individuals who make financial plans had 10 to 15% more wealth than those who did not – in other words, while wealthier individuals may become more financially literate, financial literacy also made individuals wealthier[133].

In the UK, the Financial Services Authority has developed a measure of financial literacy. Their measure identifies four areas: ‘managing money’, ‘planning ahead’, ‘choosing products’ and ‘staying informed’[138]. The questionnaire was put to a representative panel of over 5000 adults in the UK, and it revealed that while the majority of the public scored well in managing money, with 65% able to keep up with bills and credit commitments, many people scored low for planning ahead and making financial choices, indicating that people were generally poor at selecting appropriate financial products, understanding risk, and planning for the future[139]. Despite the fact that few people are financially literate, the majority of individuals rely on the advice of family and friends[140]. More financially literate individuals refer to newspapers, books, and the Internet, but even then, their complex investment choices are affected by word-of-mouth advice from friends, neighbours and even fellow church-goers[141,142].

3.2. Nudge

The dominant focus in the UK government has been on ‘nudge policies’, which seek to influence a person’s choices by framing or playing on behavioural motivations[143]. Thaler and Sunstein (2008, p.6) define a nudge as: “any aspect of the choice architecture that alters people’s behaviour in a predictable way without forbidding any options or significantly changing their economic incentives”. This means that nudge is conceptually distinct from a regulation, since to count as a mere nudge, a person must be able to easily and cheaply resist the nudge if they want to. Thus putting the fruit at eye level counts as a nudge, but banning or taxing junk food does not.
Some of the most prominent nudge policies have stemmed from the insight that people are more likely to stick with the default options on forms. Studies have found that changing the default has very large consequences for choices that people make regarding retirement savings, insurance plans, and organ donation[144,145]. For example, in Austria, consent to being an organ donor is the default option, so that not consenting requires an active decision to opt out. There the effective consent rate is 99.98%[146]. Over the border in Germany, where the default option is non-donation, the proportion of individuals who are organ donors is 12%.

In the UK, the most influential application of this idea has been the introduction of auto-enrolment in company pension schemes. In the US, automatic enrolment is predicted to cause pension participation rates to increase by 30-40%[147]. Thaler and Benartzi have devised a program known as Save More Tomorrow (SMarT) that incorporates not only automatic enrolment but also increases the default rate as the income of workers increases. Workers enrolled in SMarT have achieved saving rates of more than 13% versus an average of 5–6% for workers who did not enroll[148].

The Behavioural Insights team has run a series of trials to investigate how nudges could be used by the UK Government to reduce fraud and encourage people to pay taxes and fines[149-151]. For example, they worked with Manchester City Council to undertake a trial, sending letters to 38,000 people in receipt of council tax discounts, to ask whether they wished to reapply for the discount. Half received the existing letter, half received a nudge-inspired letter which used simpler language, made the value of the reduction statistically less salient, emphasised social norms and the fact that dishonestly was fraud. The result was a 5% drop in requests to continue the exemption – saving the Council £240,000. The Behavioural Insights Team also worked with HMRC to trail a variety of letter formats by writing to 140,000 taxpayers with outstanding taxes. Letters which stated ‘9 out of 10 Britons pay their taxes on time’, and gave statistics for tax compliance in the late-payers postcode area led to a 15% increase in payment[152]. HMRC estimates that £160 million in tax debts could be recovered if this is rolled out nationally. These examples illustrate that policymakers cannot ignore behavioural insights – frames and nudges are created whatever they do. Therefore, it is incumbent on them to avoid unwittingly introducing frames or nudges that skew behaviour in an undesired direction. For example, the name of a benefit payment will influence how it is spent, evidenced by the fact the winter fuel payment is spent disproportionately on energy – thus something as simple as an inappropriate name could significantly affect a policy’s efficacy.

While not described as nudges, similar ideas are widely used by marketing firms[80]. Unlike behavioural economics, marketing studies have traditionally drawn upon the ‘psychology of persuasion’ and ‘influence’ literatures developed by social psychologists[153]. This research helps explain the success of many marketing strategies. For example, if people commit publicly to an idea or goal, they are more likely to honour it, hence the success of weightwatchers; people tend to return a favour, hence the benefit of free samples in marketing; people do things they see others doing - especially if they like that person, hence the cult of celebrity and power of social marketing; and perceived scarcity will generate demand, hence the prevalence of ‘limited time offers’ and ‘closing down sales’[80,154]. This highlights that a breath of disciplines are relevant for behavioural insights-based policy development.

The popularity of nudge policies for politicians is obvious: they are relatively simple, inexpensive policy interventions, which can generate substantial behavioural change, and yet they do not restrict choices or change the economic incentives that people face. Unsurprisingly, their sudden popularity has attracted a diversity of critics. For example, some question whether nudge really are what they claim to be, or whether they are really a subtle form of manipulation or coercion. Goodwin argues that while not necessarily coercive, nudge policies may be manipulative if they aim to erode an individual's ability to choose freely[155]. Brookes suggests that nudges are potentially unethical if they are used by politicians to get people to adopt unpopular, or partisan policies, rather than those which are in the public interest[156]. A further issue is that the gains of some nudge policies may be short lived if people habituate to the new stimuli, or they may be negated if people react adversely when they learn the government is trying to nudge them to behave differently. These unintended consequences were recently highlighted by the media storm over the fact that a nudge-inspired trial required jobseekers to undertake a bogus psychometric test. Whatever the answers were given, the questionnaire's results painted a very positive image of the participant[157]. Critics suggested this was a waste of money, and unjust as the unemployed person was threatened with losing their benefits if they did not take part and it trivialised what may be profound self-esteem issues that many unemployed people have.

In the health literature, a number of authors have strongly criticized the government's White Paper paper 'Healthy Lives, Healthy People'[158], that suggests a role for nudge in health policy. They argue that nudges are unproven, 'eye-catching' distractions, that will divert attention and resources from tackling the true barriers to healthy living[159,160]. These critical views, are somewhat shared by the House of Lords Science and Technology Committee. The Committee's 2011 Report 'Behaviour Change' found that nudges are unlikely to be effective on their own and that the whole range of traditional, more costly, policy interventions should be considered[161]. Some suggest that instead of trying to manipulate biases, the role of government should be to educate people to help them de-bias their behaviour[162,163]. However, it is unclear whether 'de-biasing' could work given the evidence that biases remain even when economic incentives are offered to overcome them[78].

3.3. Information provision

Behavioural insights can help inform policy that aims to make information provision more effective. For example, in the health literature, there is an increasing reliance on testimonials and stories to convey information, rather than on figures and hard data[164]. Statistical information can be presented in formats that greatly enhance people's understanding of the choices they face, for instance by using natural frequencies instead of percentages or probabilities and by allowing individuals to compare their choices with those of other people[165,166]. More complex statistics relating to risk and uncertainty can be effectively conveyed using appropriate visualisations and graphics[167]. Finally, how information is framed influences how seriously people consider the message and how well they retain its information. For example, people use physical, linguistic, cultural and social cues to determine the credibility of a messenger; information that is provided by experts without vested interests, or by people who are like the target audience in some way are also deemed to be more credible[131].

These insights have been used effectively in the US, where the Consumer Financial Protection Bureau has simplified mortgage disclosure forms, and made the costs, monthly payments and risks of a mortgage loan more salient to the buyer. For example, the Annual Percentage Rate (APR) is redefined so that it includes all the up-front costs of the mortgage loan. Following a similar vein, in 1994 the FSA introduced the 'Treating Customers Fairly obligations' to require sellers of financial products to present the consumer with a Key Features Documents (KFD). The intention was to provide key pieces of information about the product (such as aims of the product and the risks involved) in a standardised format. However, a recent survey has found these have become legalistic and overly long, with only 15% being effective[168]. There are discussions underway amongst stakeholders as to how to apply the insights from behavioural economics to improve the value of KFDs[169]. Additionally, the Behavioural Insights Team is currently working with the credit card industry to introduce Annual Credit Card Statements, which contains information about fees and how to switch between credit card providers.

Regulation could also be used in situations where firms intentionally exploit consumer biases to raise profits, while reducing consumer welfare[170]. For example, the Office of Fair Trading[171] found that some firms make information unnecessarily complex, as this reduces the extent to which consumers shop around or switch[172]. Behavioural insights suggest that it is not just what information is disclosed that matters, but also how information is provided, and how complex it is for consumers to process. Government often requires firms to disclose information to consumers and regulators. However, if the format of information provided is not regulated, firms can take advantage of this by structuring information in a way that makes it hard for people to understand and react to it[163].

Another solution to cope with individual financial illiteracy is technology. Companies often have a far clearer understanding of a customer's economic behaviour than the customer themselves and they. For example, phone providers know about an individual's mobile phone and data usage and banks have a detailed understanding of an individual's financial behaviour, which far exceeds that of the individual herself. The solution could be new regulations requiring smart disclosure, which would require companies and public bodies to provide consumers or mandated third parties with the means to freely access any data held about them. This would empower consumers, as it would create a market for technology companies that could then use the data to help the consumer make better choices. For example, apps using these data could enable individual's to identify which of the 12 million mobile phone contracts is the best for them, what is the average fat content of the food they purchase, which supermarket would be cheapest for them, how much they spend each year on bills, restaurants and clothes, and whether there might be better ways to save money or different ways to use credit and debit cards. Consumers would benefit by saving money and having products that better suit their preferences and using technology in this way would help make markets more efficient.

The Government's Behavioural Insight team is pursing this idea of smart disclosure through the 'mydata' programme. Currently, 20 major businesses, covering financial services, retail, utilities, telecoms and online platforms, have agreed to work with Government on this programme. They are also working with banks on the idea of 'e-statements' that will give consumers full access to all of their transactions over the last 12 months in a portable electronic format. This data would then be able for consumer to 'plug in' to price comparison websites, money management websites and mobile apps.

3.4. Behavioural insight-inspired education

If individuals struggle with financial literacy, and technology cannot help them make better choices, it might be more appropriate to encourage people to make choices by relying on heuristics that generally work, rather than trying to teach them about complex financial concepts. This idea was recently tested in the Dominican Republic, were entrepreneurs who run small businesses, were invited to take part in one of two financial training modules. One was the standard module, teaching the fundamentals of financial accounting, the other was designed by 'ideas42', a non-profit group in the US, which aims to implement ideas from behavioural economics to alleviate social problems and poverty. Their module relied on teaching simple rules-of-thumb, without explaining the underlying accounting motivation. The standard training had no significant effect on either financial management practices or business outcomes. By contrast, the rule-of-thumb training increased the fraction of people keeping accounts and calculating revenues and those separating household and business finances by 11 percentage points each. It also raised sales during bad weeks by 18.5% relative to the comparison group[173]. The potential and scalability of such financial education in developing and developed countries seems evident.

3.5. More drastic solutions?

A more drastic alternative use of behavioural motivations, which goes far beyond nudges, is to invite individuals to enroll in programmes that use negative behavioural motivations to help them achieve their goals. Negative motivations such as loss aversion and reputational concerns are potentially more potent forces than rewards and positive framing. This idea, that negative motivations can influence behaviour more than positive encouragement, has being successfully applied by the website 'http://www.stickk.com/'. Stickk.com was set up by psychologists in the US that wanted to help individuals reach goals such as losing weight, repaying debt and quitting smoking. It does this by asking users to make a publically visible 'commitment contract', which precisely defines the individual's goal. This commitment cannot be deleted if the goal is not reached. The user is then invited to designate referees that will be asked to monitor their progress and ensure they are reporting honestly. They can invite their friends via email, Facebook or Twitter to become supporters and follow their progress. Finally, users can optionally give their credit card information so as to add financial stakes as an incentive. One particularly popular incentive is that for every missed target, the user's card information will be used to donate money to either an individual they dislike, or to whom they would be embarrassed to explain the reason for the payment (such as a parent, teacher or ex-boyfriend) or to an ‘anti-charity’ who’s views they despise. Popular anti-charities include the NRA, extreme anti-abortion groups, anti-gay groups or fundamentalist religious groups of a religion the participant do not follow[174]. Might a similar approach be used to encourage saving behaviour, bill repayment or debt avoidance?

Given that individuals possess limited financial literacy, they often make inadequate plans for retirement and inappropriate financial choices; there is a question of who pays for these bad financial choices. Left to their own devices, individuals may not save enough for retirement, may invest in assets that are either too risky or too conservative and may not make use of tax advantages or benefits. Should the individual, who through no fault of their own lacks the financial capacity to avoid such mistakes, be made to pay for them? Is that not similar to saying that the victim of a confidence trickster deserves what they get? If ultimately, taxpayers have to foot the bill when individuals make financial errors, or when firms entice individuals to take excessive risks, does this not create a mandate for governments and regulators to use more intrusive policies to prevent them making such mistakes in the first place? The economists Alesina and Lusardi, have made the controversial suggestion that because the personal and social costs of bad financial judgments are so great, just as people need a driving licence before they can drive a car, people should also be required to have a ‘financial licence’ before they are allowed to join a pension, gain credit or buy a house. They suggest that obligatory, publicly funded, financial education programmes would help protect vulnerable people and ultimately create savings for the public purse, as anyone unable to achieve the necessary level of financial literacy, would have a financial advisor to help them make appropriate financial choices[175].

Conclusion

This review has attempted to draw together diverse literatures on risky behaviour and highlight the links and complimentary ideas that exist in biological and the social science disciplines. This review has not attempted to answer, or even explicitly define the big questions facing financial regulators today. That task is for you. The review of current behavioural-insights inspired policy suggests that the engagement with these disciplines is somewhat superficial. Can we do any better? The challenge now is to draw together the different perspectives provided by these disciplines to identify whether they provide new insights that can help develop better financial risk regulations.

References

1. Krebs, J. R. Risk, uncertainty and regulation. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences* **369,** 4842–4852 (2011).
2. Jaeger, C. *Risk Uncertainty & Rational Action*. (Earthscan, 2001).
3. Kacelnik, A. Meanings of rationality. In: Hurley, S. L & Nudds, M. eds. Rational animals, *Oxford: Oxford University Press,* 87-106 (2006).
4. Grafen, A. Formalizing Darwinism and inclusive fitness theory. *Philosophical Transactions of the Royal Society B: Biological Sciences* **364,** 3135–3141 (2009).
5. Hamilton, W. D. The genetical evolution of social behaviour. I. *Journal of Theoretical Biology* **7,** 1–16 (1964).
6. Hamilton, W. D. The genetical evolution of social behaviour. II. *Journal of Theoretical Biology* **7,** 17–52 (1964).
7. Davies, N. B., Krebs, J. R. & West, S. A. An Introduction to Behavioural Ecology *Wiley-Blackwell.* (2012).
8. Parker, G. A. & Smith, J. M. Optimality theory in evolutionary biology. *Nature* **348,** 27-33 (1990).
9. El Mouden, C., Burton-Chellew, M. N., Gardner, A. & West, S. A. in *Evolution and Rationality: Decisions, Co-operation and Strategic Behaviour* (Okasha, S. & Binmore, K.) 23–49 (Cambridge University Press, 2012).
10. West, S. A., El Mouden, C. & Gardner, A. Sixteen common misconceptions about the evolution of cooperation in humans. *Evolution and Human Behavior* **32,** 231–262 (2011).
11. Gardner, A. Adaptation as organism design. *Biol. Lett.* **5,** 861–864 (2009).
12. Davies, N. B., Hatchwell, B. J., Robson, T. & Burke, T. Paternity and parental effort in dunnocks Prunella modularis: how good are male chick-feeding rules? *Animal Behaviour* **43,** 729–745 (1992).
13. Wehner, R. ‘matched filters’—neural models of the external world. *J. Comp. Physiol.* **161,** 511–531 (1987).
14. Charnov, E. L. Optimal foraging, the marginal value theorem. *Theoretical Population Biology* **9,** 129–136 (1976).
15. Waddington, K. D., Allen, T. & Heinrich, B. Floral preferences of bumblebees (Bombus edwardsii) in relation to intermittent versus continuous rewards. *Animal Behaviour* **29,** 779–784 (1981).
16. Case, D. A., Nichols, P. & Fantino, E. Pigeons' preference for variable-interval water reinforcement under widely varied water budgets. *J Exp Anal Behav* **64,** 299–311 (1995).
17. Caraco, T., Blanckenhorn, W. U., Gregory, G. M. & Newman, J. A. Risk-sensitivity: ambient temperature affects foraging choice. *Animal Behaviour* **39,** 338–345 (1990).
18. McNamara, J. M. & Houston, A. I. Risk-sensitive foraging: a review of the theory. *Bulletin of Mathematical Biology* **54,** 355–378 (1992).
19. Real, L. A. Uncertainty and pollinator-plant interactions: the foraging behavior of bees and wasps on artificial flowers. *Ecology* **62,** 20-26 (1981).
20. Tuttle, E., Wulfson, L. & Caraco, T. Risk-aversion, relative abundance of resources and foraging preference. *Behav Ecol Sociobiol* **26,** (1990).
21. Caraco, T. Aspects of risk-aversion in foraging white-crowned sparrows. *Animal Behaviour* **30,** 719–727 (1982).
22. Wunderle, J. M. & O'Brien, T. G. Risk aversion in hand-reared bananaquits. *Behav Ecol Sociobiol* **17,** 371–380 (1985).
23. Kacelnik, A. & Bateson, M. Risky Theories - The Effects of Variance on Foraging Decisions. *American Zoology* **36,** 402–434 (1996).
24. Mazur, J. E. Estimation of indifference points with an adjusting-delay procedure. *J Exp Anal Behav* **49,** 37–47 (1988).
25. Bateson, M. & Kacelnik, A. Preferences for fixed and variable food sources: variability in amount and delay. *J Exp Anal Behav* **63,** 313–329 (1995).
26. Reboreda, J. C. & Kacelnik, A. Risk sensitivity in starlings: variability in food amount and food delay. *Behavioral Ecology* **2,** 301-308 (1991).
27. Caraco, T. On foraging time allocation in a stochastic environment. *Ecology* **61,** 119-128 (1980).
28. Caraco, T. Risk-sensitivity and foraging groups. *Ecology* **62,** 527-531 (1981).
29. Stephens, D. W. The logic of risk-sensitive foraging preferences. *Animal Behaviour* **29,** 628-629 (1981).

30. Bateson, M. Starlings' preferences for predictable and unpredictable delays to food. *Journal of Economic Behavior & Organization* **53,** 1129–1142 (1997).
31. Logan, F. A. Decision making by rats: uncertain outcome choices. *J Comp Physiol Psychol* **59,** 246–251 (1965).
32. Kacelnik, A. & Bateson, M. Risk-sensitivity: crossroads for theories of decision-making. *Trends in Cognitive Sciences* **1,** 304–309 (1997).
33. Kacelnik, A. & Brito e Abreu, F. Risky Choice and Weber's Law. *Journal of Theoretical Biology* **194,** 289–298 (1998).
34. Houston, A. & McNamara, J. A sequential approach to risk-taking. *Journal of Economic Behavior & Organization* **30,** 1260–1261 (1982).
35. McNamara, J. M. & Houston, A. I. Risk-sensitive foraging: A review of the theory. *Bulletin of Mathematical Biology* **54,** 355–378 (1982).
36. McNamara, J. & Houston, A. I. A general framework for understanding the effects of variability and interruptions on foraging behaviour. *Acta Biotheoretica* **36,** 3–22 (1987).
37. McNamara, J. M. Risk-Prone Behaviour Under Rules Which Have Evolved in a Changing Environment. *Integr Comp Biol* **36,** 484–495 (1996).
38. Hsu, M., Bhatt, M., Adolphs, R., Tranel, D. & Camerer, C. F. Neural systems responding to degrees of uncertainty in human decision-making. *Science* **310,** 1680–1683 (2005).
39. Cesarini, D., Dawes, C. T., Johannesson, M., Lichtenstein, P. & Wallace, B. Genetic Variation in Preferences for Giving and Risk Taking *. *Quarterly Journal of Economics* **124,** 809–842 (2009).
40. De Neve, J. E. & Fowler, J. H. The MAOA gene predicts credit card debt. *Available at SSRN 1457224* (2009).
41. Ibañez, A., Perez de Castro, I., Fernandez-Piqueras, J., Blanco, C. & Saiz-Ruiz, J. Pathological gambling and DNA polymorphic markers at MAO-A and MAO-B genes. *Mol. Psychiatry* **5,** 105–109 (2000).
42. Frydman, C., Camerer, C., Bossaerts, P. & Rangel, A. MAOA-L carriers are better at making optimal financial decisions under risk. *Proc. Biol. Sci.* **278,** 2053–2059 (2011).
43. Ebstein, R. P., Israel, S., Chew, S. H., Zhong, S. & Knafo, A. Genetics of human social behavior. *Neuron* **65,** 831–844 (2010).
44. Benjamin, D. J. *et al.* The Promises and Pitfalls of Genoeconomics. *Annu. Rev. Econ.* **4,** 627–662 (2012).
45. Benjamin, D. J. *et al.* The genetic architecture of economic and political preferences. *Proc. Natl. Acad. Sci. U.S.A.* **109,** 8026–8031 (2012).
46. Schultz, W. *et al.* Explicit neural signals reflecting reward uncertainty. *Philosophical Transactions of the Royal Society B: Biological Sciences* **363,** 3801–3811 (2008).
47. Tymula, A. *et al.* Adolescents' risk-taking behavior is driven by tolerance to ambiguity. *Proc. Natl. Acad. Sci. U.S.A.* **109,** 17135–17140 (2012).
48. Lerner, J. S. & Keltner, D. Beyond valence: Toward a model of emotion-specific influences on judgement and choice. *Cognition & Emotion* **14,** 473–493 (2000).
49. Mohr, P. N. C., Biele, G. & Heekeren, H. R. Neural processing of risk. *J. Neurosci.* **30,** 6613-6619 (2010).
50. Platt, M. L. & Huettel, S. A. Risky business: the neuroeconomics of decision making under uncertainty. *Nat. Neurosci.* **11,** 398–403 (2008).
51. Heekeren, H. R., Marrett, S. & Ungerleider, L. G. The neural systems that mediate human perceptual decision making. *Nat. Rev. Neurosci.* **9,** 467–479 (2008).
52. Apicella, C. L., Dreber, A., Campbell, B. & Gray, P. B. Testosterone and financial risk preferences. *Evolution and Human Behavior* **29,** 384–390 (2008).
53. Coates, J. M., Gurnell, M., Rustichini, A. & McEwen, B. S. Second-to-Fourth Digit Ratio Predicts Success among High-Frequency Financial Traders. *Proc. Natl. Acad. Sci. U.S.A.* **106,** 623–628 (2009).
54. Coates, J. *The Hour Between Dog and Wolf: Risk-taking, Gut Feelings and the Biology of Boom and Bust*. (Fourth Estate, 2012).
55. Coates, J. M., Gurnell, M. & Sarnyai, Z. From molecule to market: steroid hormones and financial risk-taking. *Philosophical Transactions of the Royal Society B: Biological Sciences* **365,** 331–343 (2009).
56. Apicella, C. L. *et al.* Androgens and competitiveness in men. *Journal of Neuroscience, Psychology, and Economics* **4,** 54–62 (2011).
57. Zethraeus, N. *et al.* A Randomized Trial of the Effect of Estrogen and Testosterone on Economic Behavior. *Proc. Natl. Acad. Sci. U.S.A.* **106,** 6535–6538 (2009).

58. Wingfield, J. C., Hegner, R. E., Dufty, A. M. & Ball, G. F. The Challenge Hypothesis - Theoretical Implications for Patterns of Testosterone Secretion, Mating Systems, and Breeding Strategies. *American Naturalist* **136,** 829–846 (1990).
59. Archer, J. Testosterone and human aggression: an evaluation of the challenge hypothesis. *Neurosci Biobehav Rev* **30,** 319–345 (2006).
60. Arrow, K. J. in *Aspects of the Theory of Risk Bearing* (Saatio, Y. J.) (Helsinki, 1965).
61. Friend, I. & Blume, M. E. The demand for risky assets. *Am Econ Rev* (1975).
62. Becker, G. S. The Economic Approach to Human Behavior, *Chicago: Chicago University Press* (1976).
63. Tversky, A. & Kahneman, D. The framing of decisions and the psychology of choice. *Science* **211,** 453-458 (1981).
64. Roszkowski, M. J. & Snelbecker, G. E. Effects of 'Framing' on measures of risk tolerance: Financial planners are not immune. *Journal of Behavioral Economics* **19,** 237–246 (1990).
65. McNeil, B. J., Pauker, S. G., Sox, H. C. & Tversky, A. On the elicitation of preferences for alternative therapies. *N. Engl. J. Med.* **306,** 1259–1262 (1982).
66. Townsend, C. & Shu, S. B. When and how aesthetics influences financial decisions. *Journal of Consumer Psychology* **20,** 452–458 (2010).
67. Lichtenstein, S. Judged Frequency of Lethal Events. *Journal of Experimental Psychology: Human Learning and Memory* **4,** 551–78 (1978).
68. Gregory, R. & Mendelsohn, R. Perceived Risk, Dread, and Benefits. *Risk Analysis* **13,** 259–264 (1993).
69. Slovic, P. *The perception of risk*. (Earthscan / James & James, 2000).
70. Finucane, M. L., Alhakami, A., Slovic, P. & Johnson, S. M. The affect heuristic in judgments of risks and benefits. *Journal of behavioral decision making* **13,** 1–17 (2000).
71. Ganzach, Y. Judging Risk and Return of Financial Assets. *Organizational Behavior and Human Decision Processes* **83,** 353–370 (2000).
72. Sanchirico, C. W. Finding Error. *L Rev MSU-DCL* **1189** (2003).
73. Kamin, K. A. & Rachlinski, J. J. Ex Post ≠ Ex Ante: Determining Liability in Hindsight. *Law and Human Behavior* **19,** 89–104 (1995).
74. Taleb, N. The black swan: Why don't we learn that we don't learn. *NY: Random House* (2005).
75. Taleb, N. N., Goldstein, D. G. & Spitznagel, M. W. The six mistakes executives make in risk management. *Harvard business review,* (2009).
76. Tversky, A. & Kahneman, D. Judgment under uncertainty: heuristics and biases. *Science* **185** 1124-1131(1974).
77. Strack, F. & Mussweiler, T. Explaining the enigmatic anchoring effect: Mechanisms of selective accessibility. *Journal of Personality and Social Psychology* **73,** 437–446 (1997).
78. Furnham, A. & Boo, H. C. A literature review of the anchoring effect. *Journal of Socio-Economics,* **40,** 35-42 (2011).
79. Latane, B. & Darley, J. M. Bystander 'Apathy'. *American Scientist* , **57,** 244-268 (1969).
80. Cialdini, R. B. *Influence*. Collins Business Essentials, (2009).
81. Gintis, H., Bowles, S., Boyd, R. & Fehr, E. Explaining altruistic behavior in humans. *Evolution and Human Behavior* **24,** 153-172 (2003).
82. Fehr, E. & Gächter, S. Altruistic punishment in humans. *Nature* **415,** 137–140 (2002).
83. Fehr, E. & Fischbacher, U. The nature of human altruism. *Nature* **425,** 785–791 (2003).
84. Fischbacher, U., Gächter, S. & Fehr, E. Are people conditionally cooperative? Evidence from a public goods experiment. *Economics Letters* **71,** 397–404 (2001).
85. Bourke, A. Principles of social evolution. *Oxford: Oxford University Press* (2011).
86. Burton-Chellew, M. N. & West, S. A. Prosocial preferences do not explain human cooperation in public-goods games, **110,** 216-221 (2013).
87. Kümmerli, R., Burton-Chellew, M. N., Ross-Gillespie, A. & West, S. A. Resistance to extreme strategies, rather than prosocial preferences, can explain human cooperation in public goods games. *Proc. Natl. Acad. Sci. U.S.A.* **107,** 10125–10130 (2010).
88. Winking, J. & Mizer, N. Natural-field dictator game shows no altruistic giving. *Evolution and Human Behavior* (2013). doi:10.1016/j.evolhumbehav.2013.04.002
89. Renn, O. & Rohrmann, B. Cross-cultural risk perception: a survey of empirical studies. *Springer.* (2000).
90. Slovic, P., Kraus, N., Lappe, H. & Major, M. Risk perception of prescription drugs: report on a survey in Canada. *Can J Public Health* **82,** S15–20– S38–44 (1991).

91. Kleinhesselink, R. R. & Rosa, E. A. Cognitive Representation of Risk Perceptions: A Comparison of Japan and the United States. *Journal of Cross-Cultural Psychology* **22,** 11–28 (1991).
92. Weber, E. U. & Hsee, C. Cross-cultural differences in risk perception, but cross-cultural similarities in attitudes towards perceived risk. *Management Science* **44,** 1205–1217 (1998).
93. Bontempo, R. N., Bottom, W. P. & Weber, E. U. Cross-Cultural Differences in Risk Perception: A Model-Based Approach. *Risk Analysis* **17,** 479–488 (1997).
94. Hsee, C. & Weber, E. Cross-national differences in risk preference and lay predictions. *Journal of Behavioral Decision Making* **12** (1999).
95. Herrmann, B., Thoni, C. & Gachter, S. Antisocial Punishment Across Societies. *Science* **319,** 1362–1367 (2008).
96. Simon Gächter, B. H. Reciprocity, culture and human cooperation: previous insights and a new cross-cultural experiment. *Philosophical Transactions of the Royal Society B: Biological Sciences* **364,** 791 (2009).
97. Henrich, J. *et al.* Markets, religion, community size, and the evolution of fairness and punishment. *Science* **327,** 1480–1484 (2010).
98. Gächter, S., Herrmann, B. & Thöni, C. Trust, voluntary cooperation, and socio-economic background: survey and experimental evidence. *Journal of Economic Behavior & Organization* **55,** 505–531 (2004).
99. Henrich, J., Heine, S. J. & Norenzayan, A. Most people are not WEIRD. *Nature* **466**, 29 (2010).
100. Kahneman, D. & Tversky, A. Prospect theory: An analysis of decision under risk. *Econometrica* **47,** 263-292 (1979).
101. Bell, D. E. Regret in Decision-Making Under Uncertainty. *Operations Research* **30,** 961–981 (1982).
102. Loomes, G. & Sugden, R. Regret Theory: An Alternative Theory of Rational Choice Under Uncertainty. *The Economic Journal,* **92**, 805-824 (1982).
103. Gul, F. A theory of disappointment aversion. *Econometrica* **59,** 667-686 (1991).
104. Quiggin, J. A theory of anticipated utility. *Journal of Economic Behavior & Organization* **3**, 323-343 (1982).
105. Segal, U. Some remarks on Quiggin's anticipated utility. *Journal of Economic Behavior & Organization* **8,** 145–154 (1987).
106. Yaari, M. E. The dual theory of choice under risk. *Econometrica* **55**, 95-115 (1987).
107. Edwards, K. D. Prospect theory: A literature review. *International Review of Financial Analysis* **5,** 19–38 (1996).
108. Mehra, R. & Prescott, E. C. The equity premium: A puzzle. *Journal of Monetary Economics* **15,** 145–161 (1985).
109. Benartzi, S. & Thaler, R. H. Myopic Loss Aversion and the Equity Premium Puzzle. *The Quarterly Journal of Economics* **110,** 73–92 (1995).
110. Michenaud, S. & Solnik, B. Applying regret theory to investment choices: currency hedging and decisions. *Journal of International Money and Finance* 677–694 (2008).
111. Gigerenzer, G. & Gaissmaier, W. Heuristic decision making. *Annu Rev Psychol* **62,** 451–482 (2011).
112. Ariely, D. *Predictably irrational, revised and expanded edition: The hidden forces that shape our decisions*. (Harper, 2009).
113. Brandstatter, E., Gigerenzer, G. & Hertwig, R. The priority heuristic: Making choices without trade-offs. *Psychological Review* **113,** 409–432 (2006).
114. Gigerenzer, G. & Brighton, H. Homo Heuristicus: Why Biased Minds Make Better Inferences. *Topics in Cognitive Science* **1,** 107–143 (2009).
115. Marewski, J. N., Gaissmaier, W. & Gigerenzer, G. Good judgments do not require complex cognition. *Cogn Process* **11,** 103–121 (2009).
116. Wübben, M. & Wangenheim, F. Instant Customer Base Analysis: Managerial Heuristics Often 'Get It Right'. *Journal of Marketing* **72,** 82–93 (2008).
117. Peters, O. Optimal leverage from non-ergodicity. *Quantitative Finance* **11** 1593-1602 (2011).
118. Slovic, P., Fischhoff, B. & Lichtenstein, S. Rating the Risks. *Environment: Science and Policy for Sustainable Development* **21,** 14–39 (1979).
119. Weber, E. U. "Decision and choice: Risk, empirical studies." *International Encyclopedia of the Social and Behavioral Sciences* (2001): 13347-13351.

120. Slovic, P. Perception of risk. *Science* **236,** 280–285 (1987).
121. Kasperson, R. E. *et al.* The Social Amplification of Risk: A Conceptual Framework. *Risk Analysis* **8,** 177–187 (1988).
122. Morrall, J. F., III. Saving Lives: A Review of the Record - Springer. *Bulletin of Mathematical Biology* **27,** 221–237 (2003).
123. Godfrey, C., Parrott, S., Coleman, T. & Pound, E. The cost-effectiveness of the English smoking treatment services: evidence from practice. *Addiction* **100 Suppl 2,** 70–83 (2005).
124. Douglas, M., & Wildavsky, A. Risk and culture: an essay on the selection of technological and environmental dangers. Berkeley. *Cal.: Univ. of California Press* (1982).
125. Swedlow, B. A Cultural Theory of Politics. *APSC* **44,** 703–710 (2011).
126. Swedlow, B. Cultural Surprises as Sources of Sudden, Big Policy Change. *APSC* **44,** 736–739 (2011).
127. D, I. Understanding the Four Seasons of Risk Management. *Insurance Risk & Capital* **1-3,** (2009).
128. Underwood, A. & Ingram, D. The Full Spectrum of Risk Attitude. *The Actuary* 27–32 (2010).
129. Dyson, S., Goldspink, C. & Kay, R. Do Actuaries Have a larger Role to Play in Enterprise Risk Management. *Actuaries Australia* (2009).
130. Dolan, P., Hallsworth, M., Halpern, D. & King, D. Influencing behaviour: The mindspace way. *Journal of Economic Psychology* **33,** 264–277 (2012).
131. Dolan, P., Hallsworth, M., Halpern, D., King, D. & Vlaev, I. *MINDSPACE: influencing behaviour through public policy*. 1–96 (London: Institute for Government, 2010).
132. Galesic, M. & Garcia-Retamero, R. Statistical Numeracy for Health: A Cross-cultural Comparison With Probabilistic National Samples Statistical Numeracy for Health. *Arch Intern Med* **170,** 462–468 (2010).
133. Lusardi, A. & Mitchell, O. S. Baby Boomer retirement security: The roles of planning, financial literacy, and housing wealth. *Journal of Monetary Economics* **54,** 205–224 (2007).
134. Lusardi, A. & Mitchell, O. S. Financial literacy around the world: an overview. *Journal of Pension Economics and Finance* **10,** 497–508 (2011).
135. Stango, V. & Zinman, J. Fuzzy math and red ink: when the opportunity cost of consumption is not what it seems. (2007).
136. Behrman, J. R., Mitchell, O. S., Soo, C. K. & Bravo, D. How Financial Literacy Affects Household Wealth Accumulation. *Am Econ Rev* **102,** 300–304 (2012).
137. Lusardi, A. Household saving behaviour: the role of financial literacy, information and financial education programmes. *NEPR Working Paper 13824,* 1–44 (2008).
138. Kempson, E., Collard, S. & Moore, N. Measuring financial capability: An exploratory study for the Financial Services Authority. *Consumer Financial Capability: Empowering European Consumers* 39 (2006).
139. Financial Services Authority. *Levels of Financial Capability in the UK: Results of a baseline survey* 47 (2006).
140. Van Rooij, M., Lusardi, A. & Alessie, R. Financial literacy and stock market participation. *Journal of Financial Economics* **101**(2) 449-472 (2011).
141. Hong, H., Kubik, J. D. & Stein, J. C. Social Interaction and Stock-Market Participation. *The Journal of Finance* **59,** 137–163 (2004).
142. Brown, J. R., Ivković, Z. & Smith, P. A. Neighbors Matter: Causal Community Effects and Stock Market Participation. *The Journal of Finance* **63,** 1509–1531 (2008).
143. Thaler, R. H. & Sunstein, C. R. Nudge: Improving decisions about health, wealth, and happiness. (2008). Yale University Press.
144. Goldstein, D. G., Johnson, E. J., Herrmann, A. & Heitmann, M. Nudge your customers toward better choices. *Harvard Business Review* **86,** 99–105 (2008).
145. Scarbecz, M. 'Nudging' your patients toward improved oral health. *J Am Dent Assoc* **143,** 907–915 (2012).
146. Johnson, E. J. & Goldstein, D. Medicine. Do defaults save lives? *Science* **302,** 1338–1339 (2003).
147. Crossley, T. F. & Emmerson, C. Raising household saving. *The British Academy* (2012).
148. Thaler, R. H. & Benartzi, S. Save More Tomorrow™: Using Behavioral Economics to Increase Employee Saving. *J. Polit Econ* **112,** S164–S187 (2004).
149. Leviner, S. An overview: a new era of tax enforcement–from 'big stick' to responsive

regulation. *Regulation & Governance* (2008).
150. Robben, H., Webley, P. & Weigel, R. H. Decision frame and opportunity as determinants of tax cheating. *Journal of Economic Psychology* **11,** 341–364 (1990).
151. Frey, B. S. & Torgler, B. Tax morale and conditional cooperation. *Journal of Comparative Economics* **35,** 136–159 (2007).
152. Cabinet Office. Applying behavioural insights to reduce fraud, error and debt. 1–38 (2012).
153. Schultz, P. W., Nolan, J. M., Cialdini, R. B., Goldstein, N. J. & Griskevicius, V. The Constructive, Destructive, and Reconstructive Power of Social Norms. *Psychological Science* **18,** 429–434 (2007).
154. Cialdini, R. B. & Goldstein, N. J. Social Influence: Compliance and Conformity. *Annu Rev Psychol* **55,** 591–621 (2004).
155. Goodwin, T. Why We Should Reject 'Nudge'. *Politics* **32,** 85–92 (2012).
156. Brooks, T. Should We Nudge Informed Consent? *The American Journal of Bioethics* **13,** 22–23 (2013).
157. Jobseekers made to carry out bogus psychometric tests | Society | The Guardian. *guardian.co.uk* at <http://www.guardian.co.uk/society/2013/apr/30/jobseekers-bogus-psychometric-tests-unemployed>
158. Department of Health. *Healthy lives, healthy people: our strategy for public health in England*. (2010).
159. Marteau, T. M., Ogilvie, D., Roland, M., Suhrcke, M. & Kelly, M. P. Judging nudging: can nudging improve population health? *BMJ* **342,** d228 (2011).
160. Bonell, C., McKee, M., Fletcher, A., Wilkinson, P. & Haines, A. One nudge forward, two steps back. *BMJ* **342,** d401–d401 (2011).
161. House of Lords, Science and Technology Committee *Behaviour Change*. (2011).
162. Schwarz, N., Sanna, L. J., Skurnik, I. & Yoon, C. 1. Metacognitive Experiences and the Intricacies of Setting People Straight: Implications for Debiasing and Public Information Campaigns. *Advances in Experimental Social Psychology* **Vol 39,** 127–161 T2 – (2007).
163. Leicester, A., Levell, P. & Rasul, I. *Tax and benefit policy: insights from behavioural economics*. 1–96 (IFS Commentary C125, 2012).
164. Holmes-Rovner, M. & Stableford, S. Evidence-based patient choice: a prostate cancer decision aid in plain language. *BMC Med Inform Decis Mak* **5,** 16 (2005).
165. Gigerenzer, G. Calculated risks: How to know when numbers deceive you. *Simon & Schuster* (2003).
166. Gigerenzer, G. & Edwards, A. Simple tools for understanding risks: from innumeracy to insight. *BMJ* **327,** 741–744 (2003).
167. Spiegelhalter, D., Pearson, M. & Short, I. Visualizing uncertainty about the future. *Science* **333,** 1393–1400 (2011).
168. Financial Services Authority. Good and poor practices in Key Features Documents. 1–38 (2007).
169. Ritchie, A. *et al. Transforming consumer information discussion paper*. 1–80 (Insitute and Faculty of Actuaries, London, 2012).
170. Armstrong, M. & Huck, S. Behavioral economics as applied to firms: a primer. CESifo Working Paper Series No. 2937. (2010).
171. Bennett, M. & Fingleton, J. Behavioral Economics In Consumer Protection And Competition Law: What Does Behavioral Economics Mean for Competition Policy? *Competition* (2010).
172. Ellison, G. & Ellison, S. F. Search, obfuscation, and price elasticities on the internet. *Econometrica* **77,** 427–452 (2009).
173. Drexler, A., Fischer, G. & Schoar, A. *Keeping it simple: Financial literacy and rules of thumb*. (Centre for Economic Policy Research, 2010).
174. Selinger, E. & Whyte, K. P. What Counts as a Nudge? *The American Journal of Bioethics* **12,** 11–12 (2012).
175. Alesina, A. & Lusardi, A. Driving Your Financial Investment? Perhaps a License is Needed. *Dartmouth College, mimeo* (2006).