Reasoning about extreme events

A review of behavioural biases in relation to catastrophe risks

Knowledge Transfer Network

Financial Services

THE LIGHTHILL RISK NETWORK

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Contents

01 Executive summary

The present report outlines behavioural biases studied in the literature in relation to the way people reason about and respond to catastrophe risks. The project is led by the Lighthill Risk Network, in collaboration with a team of social and behavioural researchers from the University of Kent.

The aim of this report is to increase awareness of selected behavioural risks, and to highlight ways how biases can affect insurance purchases and underwriting decisions. The report focuses on catastrophe risk as a priority area for the insurance industry, and because catastrophe risks have been more widely studied in the literature than other types of risk.

PEOPLE ARE SWAYED BY INFORMATION THAT CAPTURES ATTENTION EASILY

The availability heuristic operates when decision makers give too much weight to salient information. This can lead to overestimates of the likelihood of recent events, and to hikes in demands for insurance after a disaster as well as the overweighting of recent losses on the side of insurers. When estimating the likelihood of events such as natural disasters people need to be aware of the gambler's fallacy, or the mean reversion bias, both of which occur when people apply statistical principles erroneously as rules of thumb.

SMALL PROBABILITIES ARE MISJUDGED EASILY

Small probabilities can be misjudged in different ways. When probabilities are clearly specified, decision makers often tend to overweight outcomes associated with small probabilities. Certain procedures for eliciting probability estimates from experts can, in some context, also result in misjudgements. When people draw on their own personal experience, events with small probabilities are easily ignored or downplayed. This can lead to serious misperceptions in the context of catastrophe risks.

THE TIME HORIZON CHANGES RISK PERCEPTIONS

The subjective values attached to gains and losses decay over time and at different rates. Time dependent changes in values can lead to myopic risk behaviours and decisions. The immediate 'loss' of purchasing insurance (or reinsurance) looms large compared to the abstract benefit one may receive in the future if the insurance covers for a loss. Time-dependent changes can also have adverse effects on risk mitigation. Planning myopia occurs when outcomes are considered over a too restricted time horizon.

LOSSES LOOM LARGE IN RISK DECISIONS

Various biases arise because people overweight losses relative to gains. This so-called loss aversion plays a role in a variety of phenomena ranging from risk mitigation to insurance pricing. Loss aversion can explain why individuals or institutions are often reluctant to change the status quo, or continue to invest in activities in spite of escalating costs. The bias also explains why people are unwilling to accept short periods of losses, even in contexts where arguably this does not make much sense (e.g., an annual loss due to a 1-in-50 year's event).

MISPERCEPTIONS OF THE PAST CAN CREATE DELUSIONS ABOUT THE FUTURE

After the fact people often have a distorted perception of their previous views. This creates the false belief that an outcome has been known 'all along'. This illusion can make events such as catastrophes seem more predictable than they actually are. It can also make people overlook warnings when an event is preceded by many false alarms. The bias can also impede learning from the failures of others.

INSURERS NEED TO KNOW HOW MUCH PRICES HAVE BEEN ADJUSTED

Actuaries tend to anchor prices on the expected value and then adjust the recommended price if there is uncertainty or ambiguity involved, as it is often the case for catastrophe risks. Underwriters also tend to increase premiums to account for ambiguity. Re/insurers may benefit from objective standards to guide price adjustments. Other anchors such as brokers' appraisals or the lines written on other risks may also influence pricing decisions.

CATASTROPHE MODELLING CANNOT REMOVE ALL UNCERTAINTIES

There are different sources of uncertainty built into the process of modelling extreme events. A high level of expertise is needed to understand the assumptions that underlie catastrophe models. Uncertainties are inherent in the modelling of extreme events, and relatively small deviations from the model parameters can have a very large impact. Biases make supplementing modelling outcomes with human judgements a challenge.

INTERVENTIONS ARE AT HAND BUT NEED TO BE TESTED IN THE INSURANCE UNDERWRITING CONTEXT

A number of training and intervention techniques have been explored in the literature, including the use of multiple alternative scenarios, statistical reasoning, or changing the representation of probabilities, to name a few examples. However, no single intervention can circumvent all kinds of biases. Many interventions are domain specific and their effectiveness in the insurance underwriting setting is yet to be established.

A COMBINATION OF QUANTITATIVE MODELLING AND HUMAN JUDGMENT IS NEEDED, BUT MANY ISSUES REMAIN

Not enough research is taking place in actual insurance underwriting settings. It is difficult to establish objective criteria to evaluate the goodness of catastrophe risk decisions. A combination of quantitative models and human judgments appears to be the way forward, but raises the question how biases can be identified and counteracted. The industry would benefit from guidelines when and how modelling outcomes should be adjusted.

02

Introduction

At the time of writing these lines superstorm Sandy still rages across the East Coast of America. The events surrounding the largest Atlantic hurricane on record demonstrate once again the need for better understanding of catastrophe risks. Sandy is just the latest example of a chain of natural catastrophes that highlight limitations in our ability to forecast catastrophe risks. By definition catastrophe risks are low probability events that are notoriously hard to predict; not only on the basis of catastrophe models. When people reason about rare events, they often fall prey to a number of mental biases. Human factors in the context of catastrophe risks have implications for re/insurers, ranging from the decision to purchase insurance to insurance pricing and underwriting. This report provides a comprehensive summary of key behavioural biases that researchers have examined in relation to catastrophe risks. The aim of the report is to increase awareness of behavioural risks among the re/insurance industry, and to explain how biases can affect how people perceive and respond to catastrophe risks. The report also offers an integration of how human factors may interact with quantitative catastrophe models and argues that steps need to be taken to combine the two areas. At the end, we discuss possible de-biasing techniques, which may be used to ameliorate the negative effects of cognitive biases, and suggest important avenues for future research.

03 Availability Heuristic

The availability heuristic describes a potential bias when people reason about uncertainties. It refers to the tendency for people to respond more strongly to risks when instances of those risks are more available to them, from memory, from imagination, from the media, from general social discourse or from their beliefs about the world. Put differently, the availability heuristic is at work when decision makers base their judgments on information that more easily captures their attention.

In the context of catastrophe risks, the availability heuristic can lead decision makers to overestimate the likelihood of a catastrophe re-occurring due to the saliency of a recent disaster. For example, the number of flood policies sold correlates with the volume of flood losses during the previous year, which can be attributed to the availability heuristic (Browne & Hoyt, 2000). Other research has shown that prior to the Loma Prieta earthquake 34% of residents of two Californian counties considered earthquake insurance unnecessary, whereas in 1990 after the earthquake, this figure dropped to only 5% (Kunreuther, 1996; see also Palm, 1995). Similarly, Kunreuther (2002) connected the availability bias with the increased reluctance of people to fly after 9/11. The salience of the recent terrorist attack led people to overestimate the chance of being in a hijacked plane.

The availability heuristic also affects industry experts. For example, natural disasters feature prominently in siting decisions for new technology such as liquefied natural gas (LNG) containers (Kunreuther, Linnerooth, & Vaupel, 1984). The bias is spurred by the limited availability of historical records, which makes it very difficult to judge the frequency of rare events such as major industrial accidents or natural catastrophes. The media can also fuel the availability bias in people (Maguire & Albright, 2005). For example following an escaped prescribed fire in Michigan, the majority of homeowners thought that prescribed fires were dangerous and likely to escape, which goes against actual figures showing that 99% of prescribed fire happens without an incident (Winter & Fried, 2000).

Experts have argued that insurers tend to overweight recent losses, and explained this tendency with the availability bias. For example, Kunreuther and Pauly (2006) attributed the increase in premiums after hurricane Andrew to the heightened salience of the disaster. In some circumstances, insurers may stop underwriting certain risks altogether, such as after 9/11 when the insurance industry became very risk averse in relation to insuring against terrorism (Cutler & Zeckhauser, 2004). Similarly, reinsurer prices tend to drop with greater distance to a disaster, which may not only reflect the presence of excess insurance capital but also the tendency to overweight recent events when estimating risks.

In the context of dealing with uncertainties and random fluctuations, people sometimes apply, consciously or unconsciously, crude statistical rules, which can also foster biases and errors. For example, the opposite of the availability bias can occur in something known as the gambler's fallacy effect. It describes a tendency of decision makers to underestimate the probability of a repetition of an event that has just happened (Cohen, Etner, & Jeleva, 2008). The insurance equivalent of the gambler's fallacy occurs when an insured, or an insurer, assumes that an insurable event will occur because the last insurable event of the same kind was a long time ago; or alternatively the insurer assumes that the event will not occur because it has occurred recently. Natural disasters are often prone to this type of bias. For example when a natural disaster strikes people assume that it will not happen again in the near future (Cortner, Gardner, & Taylor, 1990; Gardner & Cortner, 1988). Related to the *gambler's fallacy* is the '*mean-reversion bias*', whereby decision makers assume that over time, a trend has to return to the mean. For example, after an 'unusually' high loss, decision makers may succumb to the false belief that disasters will return to 'normal'. Chains of 1 in 100 or 1 in 500 year events illustrate the futility of this belief, in particular in the context of catastrophe risks. For example, Iowa, Missouri, and Wisconsin saw a string of 'century' floods in 2008, 2010, and 2011.

04 Small Probabilities

People tend to misjudge low probability events. Behavioural decision research has been dominated by the view that people give undue weight to rare events, leading decision makers to overestimate low probabilities, and give too much weight to rare events in decision processes. And yet, there are many examples in real life in which decision makers failed to account for rare, high impact events ("black swans", see Taleb, 2007). An example of a black swan event which elicited lots of emotional reactions from people is the mad cow disease within the realm of GM (genetically modified) livestock. Below, we outline when and why rare events are often misunderstood.

WHEN SMALL PROBABILITIES ARE GIVEN TOO MUCH WEIGHT:

Rare events are overweighted *when prior probabilities are explicitly specified*. This is akin to the context in which many decision makers operate: analysts provide estimates[1] of the likelihood of particular outcomes, which then form the basis for subsequent decisions. In such a context decision makers tend to give outcomes with low probabilities too much weight than what would be justified if decisions were completely rational. There are several reason why this tends to be the case.

One factor that contributes to the overweighting of rare events is the aforementioned availability heuristic. When unlikely events are explicitly stated the outcomes of these events become salient and capture people's attention. What is more, rare events such as disasters or catastrophes often tend to elicit an emotional response, even though the associated likelihoods may be small. Thus, although people also tend to overestimate events that do not elicit strong emotional reactions, misrepresentations of small probabilities are often especially pronounced for events that invoke fear and dread. A good illustration is the 'One Percent Doctrine' put forward by Vice President Dick Cheney in the aftermath of 9/11, where Cheney announced that a likelihood of 1% of a terrorist activity must be treated as a 'certainty'.

The mind places boundaries on the extent to which people can 'handle' numerical information. Mental processes are ill equipped to deal with rare events (save a few exceptions that involve strong physical reactions, for example food poisoning). When reasoning about rare events, these events tend to form a mental cluster of 'unlikely' events in people's minds. This is problematic because the category is broad and encompasses events that have more sizeable probabilities (e.g., as much as 20%, see Lichtenstein & Newman, 1967). Consequently, mental clustering or categorization can contribute to the overweighting of small probabilities. Decision makers are also more sensitive to changes away from 0 (e.g., 0% vs. 0.01%, as compared to 60% vs. 60.01%), because these changes imply the 'possibility' that a negative event might occur. For example, one study looked at how much money consumers are willing to pay to offset the risks posed by an insecticide (Viscusi, Magat, & Huber, 1987). Consumers with children were willing to pay $12.38 instead of $10 for a bottle of insecticide that reduced the risk of injury from 15/10000 to 5/10000, but $18.09 for a bottle that completely eliminated all risks. These figures show that people have an aversion to the 'possibility' of a loss.

Research has shown that the overweighting of small probabilities can lead people to insure against small risks (such as the breakage of a house appliance), to take deductibles that are too small, or to insure against events that do not change the marginal utility[2] of their income (Cutler & Zeckhauser, 2004)

So far we have focused on situations when small probabilities are known. Preceding this step, however, risk professionals have to estimate the probability that an insured event occurs. In practice, this often implies assigning probabilities to a *set of exclusive and exhaustive events*. When judging the likelihood of a series of concrete events in probability elicitation[3], people often start by assigning equal probabilities to all possible events and then adjust the probabilities to derive the final estimates. This process is likely to lead to overestimates of small probabilities, especially when the number of possible outcomes is small. Individuals may also fall prey to overestimation biases because their exposure to reports of an event exceeds the actual occurrence of the event. For example, people's fear of crime in the UK bears little relation to actual crime

1 Decision makers often prefer point estimates over confidence intervals, which can also reinforce misrepresentations.

2 The marginal utility of income describes the incremental change in utility (or satisfaction) that comes with a unit change in income.

3 When data are sparse or there is conflicting evidence experts have to judge potential outcomes and associated probabilities in a process called probability elicitation.

statistics. People are more frequently exposed to crime in the media than what would be justified based on actual crime figures. This selective exposure provides one explanation for the discrepancy between people's perceptions and actual crime figures.

WHEN SMALL PROBABILITIES ARE GIVEN TOO LITTLE WEIGHT:

As mentioned previously much of behavioural decision research has focused on instances in which small probabilities tend to be overweighted. Recently, researchers began to explore '*decisions from experience*' (e.g., Hertwig & Erev, 2009), which denotes situations in which small probabilities are underweighted. People often have to judge probabilities based on previous encounters with an event. In such a context, events that occur rarely tend to have a diminished impact on decisions and small probabilities are often underweighted. This bias can pose a significant risk when formal methods are insufficient to predict future events, or when decision makers rely on their own personal experience to inform their decisions. For example, insurers may decide that paying £20 million for 10 years reinsurance during which they have not incurred any losses is too high. In this instance insurers would be making 'decisions from experience', and they would be likely to underestimate the actual occurrence of rare events.

Only a small number of studies have looked at the phenomenon of small probabilities in the insurance context. We know, however, that people are reluctant to purchase insurance for risks whose subjective odds are very low [called 'threshold models of choice'] (Kunreuther, Meyer, & Michel-Kerjan, 2012). Catastrophe events fall under this remit. For example, in a laboratory experiment a majority of participants bid zero for insurance because they felt the probability of loss was low enough not to need insurance to protect themselves (McClelland, Schulze, & Coursey, 1993). Experts can also fall prey to this bias of small probabilities. Prior to the 1984 Bhopal accident many chemical firms underestimated the chances of such an accident so they were not prepared for it (Bowman & Kunreuther, 1988). Risk experts also underestimated the potential risk of future terrorist attacks after the 1993 terrorist attack on the World Trade Centre. Even after 1993 terrorism was covered as an unnamed peril in many commercial insurance policies in the USA, so insurers were liable for losses from terrorism, which after 9/11 cost the insurance industry $35 billion in claims (Kunreuther & Pauly, 2006; Kunreuther & Michel-Kerjan, 2010).

RELATED CONSIDERATIONS:

When dealing with small probabilities people can get the false assumption they are protected and safe. A classic example here is the 'levee effect', which describes the sense of false security that residents of flood-prone areas have after the government builds levees in their area. The building of levees leads to more buildings being built in flood areas, and also under-mitigation of existing structures because now residents have the sense that the probability of them suffering damage from a catastrophe is significantly reduced [e.g., New Orleans] (Burby, 2006; Kunreuther, Meyer, & Michel-Kerjan, 2012).

It is also important to note that when dealing with potential losses people are more ambiguity averse when probabilities are small and when potential losses are large (Einhorn & Hogarth, 1985, 1986; Hogarth & Einhorn, 1990). Table 1 below illustrates two main sources of ambiguity for insurers: how well the likelihood of an event is specified, and the extent of the insured loss. Both sources of uncertainty affect the pricing recommendations of insurance professionals. In one study by Cabantous and colleagues (2011) insurers indicated the premiums they would charge to clients based on different risk estimates where two actuaries either agreed on a risk (1%), or recommended a range of probabilities (0.5%-2%). In a last group, the actuaries made precise risk estimates but the estimates differed from one another (0.5% and 2%), thus creating uncertainty from conflicting messages. Uncertainty always translated into higher premiums. In the case of catastrophe risks, conflicting estimates were disliked more than ambiguous estimates and resulted in the highest premiums. The insurers forgave the actuaries for their disagreement, but only in the context of catastrophe risks. In the case of non-catastrophe risks, conflicting estimates were interpreted as signs of incompetence (Cabantous, Hilton, Kunreuther, & Michel-Kerjan, 2011).

Just like underwriters, actuaries also respond to uncertainties surrounding the probability or the extent of insured losses by adjusting their premium recommendation upward (Cabantous et al., 2011). The same applies to reinsurance underwriters. For these individuals the perceived credibility of the lead underwriter provides another source of ambiguity (Kunreuther, Hogarth, & Meszaros, 1993).

TABLE 1: TWO SOURCES OF UNCERTAINTY IN THE INSURANCE CONTEXT. ADAPTED FROM KUNREUTHER, HOGARTH, AND MESZAROS (1993)

PROBABILITY \ LOSS	KNOWN	UNCERTAIN
UNCERTAIN	NEW PRODUCT DEFECTS; SATELITTE	EARTHQUAKE; INDUSTRIAL WASTE
KNOWN	LIFE; AUTOMOBILE	MEDICAL CARE; ACCIDENTS

In another study, professional underwriters set 'pure' premiums for catastrophe and non-catastrophe risks, excluding expenses, commissions, taxes, and so forth (Kunreuther, Meszaros, Hogarth, & Spranca, 1995). A certain loss was defined as $1 million, while the uncertain loss ranged from $0 to $2 million. The probability of the event was $p = .01$, and either certain (agreed among experts) or uncertain (not agreed among experts). In the context of non-catastrophe risks (an unspecified event), premiums ranged from $15,900 for the certain risk to $27,000 for the most uncertain risk. In the context of a natural disaster with the same probabilities and potential loss, these figures further increased to $19,600 for the certain risk to $29,400 for the uncertain risk. The discrepancy between catastrophe and non-catastrophe risks, even in the context of well-defined losses and probabilities, is noteworthy and demonstrates insurers' unease with catastrophe risks.

05 Temporal Discounting

Temporal discounting refers to the fact that the greater the delay to a future reward, the lower its present, subjective value (Green, Myerson, & McFadden, 1997). Thus, people are influenced more by cues that are concrete and immediate than those that are abstract and delayed. This is somewhat rational, in so far that our cognitive systems are tuned to pay more attention to the present so as to survive; however numerous studies have shown that temporal discounting in humans is 'hyperbolic', which means that discount rates in the more proximate future are steeper than discount rates in the distant future. Hyperbolic discounting is a complex concept that is perhaps best understood with an example: when faced with the choice between a £100 payout today or £200 in two years' time, many people would opt for the instant reward. However, when faced with the choice between £100 in six years' time or £200 in eight years' time, the same people are more inclined to opt for the larger, delayed reward. One way to think about hyperbolic discounting is that short- as compared to long-term pay-offs tend to elicit more myopic behaviours (Mazur, 1987). Thus risk decisions that seem sensible in a given moment may seem irrational from a more distant perspective.

It has also been shown that gains are discounted more than losses (Thaler, 1981). This can lead people to engage in seemingly irrational behaviours as immediate gains are given preference over more distant losses. This has implications for remunerations and bonuses, for example, which are often tied to a shorter time span than losses that arise from rare events. The concept of temporal discounting suggests that misperceptions can arise when there are different timeframes for gains and for losses. Discounting is also more pronounced in contexts where the default is to receive something now (e.g., a premium) than when the default is to receive it later (e.g., a pension) (Loewenstein, 1988).

Since risks by definition involve potential losses temporal discounting is an important concept for risk professionals. (Re)insurers need to trade off instant gains (premiums) against potential distant losses, while insureds need to weigh losses (the costs of an insurance) against potential gains (the costs of an insured event recovered from the insurer). For example, residents living in hurricane risk areas must decide whether to mitigate and insure their property against something that may happen in the future (Kunreuther, Meyer, & Michel-Kerjan, 2012). The immediate loss of purchasing insurance can loom large compared to the abstract benefit they may receive in the future (a benefit that residents in any case would like to avoid, hoping that a major catastrophe is not going to happen to them). Thus, residents may be reluctant to mitigate and insure against catastrophes. The same principle can be applied to reinsurance purchases. Insurers of catastrophe risks need to trade off the immediate cost of the reinsurance against the potential future gain if the insured event occurs (i.e., the monies recovered from the reinsurer). In this context the immediate loss of purchasing reinsurance may loom large, in particular when markets are soft and insured events out of sight.

Temporal discounting is also relevant for risk mitigation. A striking example is given by the failure to amend evacuation plans in New Orleans prior to hurricane Katrina. A full-scale evacuation simulation was carried out two months before Katrina which identified weaknesses; however nothing was done to mitigate those weaknesses, despite the fact that New Orleans was entering a storm season, and despite the knowledge of what might happen if a catastrophe the size of Katrina happens. Kunreuther and colleagues (2012) argue that emergency planners and New Orleans Mayor's Office understood the risks well; however they were faced with an ambiguity of what kind of investment and when they should undertake it, so they decided to defer the decision for improvements in evacuation to the future.

Another temporal bias influencing decision makers is '*planning myopia*', which is the tendency to consider consequences over a too restricted time horizon. In terms of mitigating or purchasing insurance residents living in risk prone areas may underestimate the longevity of their tenancy and thereby downplay the need for mitigation (Kunreuther, Meyer, & Michel-Kerjan, 2012). Kunreuther (2006) suggests that one of the reasons residents in the New Orleans area prior to Katrina failed to mitigate was because of myopia (see also, Kunreuther, Onculer, & Slovic, 1998; Meyer & Hutchinson, 2001). Kunreuther and Michel-Kerjan (2010) further surmise that planning myopia could be connected to the inadequate mitigation against the 9/11 terrorist attacks and most recently the BP Oil spill in 2010.

06 Loss Aversion

Loss aversion refers to the greater sensitivity of stakeholders to decreases, as opposed to increases in their wealth (Tversky & Kahneman, 1991). In other words the pain associated with a potential loss is greater than the amount of pleasure experienced from an equivalent gain (Tversky & Kahneman, 1991). Because people despise losses, they are even willing to take bets with high stakes if this gives them a small chance to avoid a loss. Gambling motivated by a desire to recoup losses features prominently in famous cases of rogue trading, including Jérôme Kerviel of Société Générale, or most recently Kweku Adoboli of UBS. In the context of natural disasters, catastrophe risk residents of hazard prone areas such as California and Florida often avoid mitigating and buying insurance because they are loss averse (cf. Kunreuther & Pauly, 2006). The same phenomenon may affect the decision of insurers to purchase reinsurance. Loss aversion can be related to temporal discounting whereby a loss that is experienced now (such as a financial loss due to purchasing insurance) will loom larger in people's minds than the potential gain later on.

Loss aversion also affects insurers' pricing decisions regarding catastrophe risks. As mentioned earlier, actuaries and underwriters tend to charge considerably higher premiums for catastrophe risks compared to other non-specified risks, and this has been connected to the fear of experiencing bankruptcy when very large risks are involved (Mayers & Smith, 1990). In a related vein, research has suggested that catastrophe bond investors tend to overweight small probabilities of losses and demand a high return (Bantwal & Kunreuther, 2000).

Loss aversion also relates to the status quo bias, which is the preference for things to stay the same. Johnson and colleagues (1993) describe a study on purchases of car insurance in the states of Pennsylvania and New Jersey. In New Jersey motorists have to pay additionally to gain the right to sue, whereas in Pennsylvania this right is the default, which can be given up in exchange for a cheaper policy. In an extraordinary demonstration of how framing is ubiquitous for the status quo bias, only 20% of New Jersey motorists chose to pay for the right to sue, whereas 75% of Pennsylvania motorists retained the right to sue (Insurance Information Institute, 1992). While motorists in New Jersey could gain the right to sue, motorists in Pennsylvania could lose the right to sue. Because losses loom larger than gains, motorists from Pennsylvania were more inclined to maintain the status quo.

The '*sunk cost bias*' describes another instance of the status quo bias linked to loss aversion. Sunk costs arise when costs incurred in the past are used as a justification to continue investing in suboptimal projects or strategies in the future (in the hope to avert a large loss). Over time, sunk costs increase, making it increasingly difficult to abandon a sub-optimal strategy. Technology projects are often prime examples of sunk cost biases. Surveys have shown that 30-40 percent of IT projects tend to suffer from some form of escalation of previous commitments (Keil, Mann, & Rai 2000).

Another related phenomenon is *myopic loss aversion*, which describes the fact that investors are particularly concerned with the potential for a short term loss, even in the context of long-term investments (Thaler, Tversky, Kahneman, & Schwartz, 1997). Myopic loss aversion fosters an unwillingness to accept short periods of losses. The phenomenon of myopic loss aversion has been related to the pricing of catastrophe bonds. Although pricing decisions should be based on a long time horizon (e.g., a 30-year return), investors seem reluctant to accept short periods of losses and focus too much on a one-year return (Bantwal & Kunreuther, 2000), which is irrational in the context of very rare events.

07 Hindsight Bias

People often believe events are more predictable than they really are. After an event has occurred, people believe they *knew* the outcome of an event before it actually happened. Fitting one's previous views after the fact reinforces the illusion that one's views or judgments are correct. It also provides a false sense of being able to predict the future. In risk management people who succumb to the hindsight bias overestimate their capacity to predict and manage risks. This false perception can cloud judgments about future risk behaviour.

Kunreuther and colleagues (2012) cite evidence for the hindsight bias amongst residents of South Florida prior to hurricane Wilma in 2005. Despite the salience of hurricane Katrina that had occurred recently, many South Florida residents decided that they were sufficiently prepared for the approach of Wilma. There had been seven false-alarms in the previous two years. In hindsight, residents benefited from not investing in risk mitigating measures, and each false alarm reinforced the view that they 'knew' all along that no disaster would happen. Confident in their own predictions, many disregarded the latest warnings, and did not prepare for the approaching hurricane which jeopardised their safety. When it comes to natural disasters it is often the case that forecasted events do not occur. Thus, it is not difficult for decision makers to succumb to the hindsight bias and become overly confident in their own ability to predict catastrophes (or the absence thereof).

Because the hindsight bias leads people to overestimate their capacity to predict and manage risks, it can dampen the motivation to learn from others. Inadequate measures are often taken in response to catastrophes, and yet people often discard other people's (painful) experiences as they 'know it better'. For example, in one laboratory study researchers investigated people's ability to learn optimal levels of investment required to protect a property from hurricane damage (Meyer, 2006). The results showed that decision makers increased their investment in mitigation only after having suffered personal losses in the previous period. Other people's losses had little impact on people's risk decisions. This has implications for the insurance and reinsurance industry, since vicarious learning would be a valuable source of information when making decisions regarding catastrophe risks. Thus, insurers would be ill advised to ignore the pitfalls of their competitors.

The hindsight bias may also preclude people from using catastrophe models in their decision making. After all it is easier to fit one's previous views after the fact than to change the outcome of catastrophe models. This may lead (re)insurance professionals to believe that they can predict the future better than catastrophe models.

08 Anchoring

Anchoring describes the process of using a starting point for evaluating or estimating unknown values. The initial value provides an 'anchor' for people's final estimates. For example, when estimating risks, people assign a particular value as the place from which they start and adjust their probability estimates.

A number of studies have shown how anchoring affects insurers' price and premium setting. For example, one study asked actuaries to set premiums for specific ratios (Hogarth & Kunreuther, 1992). The actuaries said that they anchored on expected value and adjusted the recommended price upward if there was ambiguity involved. Similarly, Lemaire (1986) observed that actuaries use expected value as a reference point to set premiums, which they then increase when there is ambiguity involved. Indeed, insurers will only take risks into their portfolio that are ambiguous if the premium is increased relative to the expected loss.

While the practice of anchoring prices to expected values seems perfectly sensible there are also drawbacks. For example, insurers may not be aware of how much prices have been adjusted, nor whether the adjustments are sufficient given the level of ambiguity involved. In a study involving catastrophe risk, Kunreuther and colleagues (1993) found that actuaries often tend to set a higher anchor to accommodate ambiguity, and underwriters, sometimes unaware of this adjustment, are inclined to do the same. Reinsurers in turn may also increase the premium due to their own perceptions of ambiguity and loss aversion. Arguably, transparency in the extent to which premiums are adjusted, and on what grounds, is beneficial for (re)insurers, not least to establish their own solvency risk. Transparency may also increase the desire for objective standards to guide price adjustments such as (statistical) confidence levels. This would be in the spirit of catastrophe modelling, although (re)insurers also need to be aware of, and ideally establish protocols to account for, the uncertainties inherent in modelling extreme events.

So far we have focused on instances where premiums are anchored on the expected loss, which is standard practice. There is a good reason to assume that other values, even arbitrary ones, may influence (re)insurers pricing decisions. Anchoring is a pervasive phenomenon that affects almost any realm of human judgments and behaviour. For example, research has shown that judges' sentencing decisions can vary considerably depending on the anchor set by a prosecution's request, all else being equal. Thus, it is not a far stretch to assume that (re)insurers are equally influenced by a range of anchors such as the brokers' appraisals, lines written on other risks, or some industry 'standard', to name a few examples.

Related to anchoring is the tendency to use reference points in decision making. For example, a $20,000 investment may be thought of as affordable by those who frame it as a large improvement, while it may be considered unaffordable by those who frame it as a small repair (Kunreuther, Meyer, & Michel-Kerjan, 2012). More generally, the assessment of something as being 'cheap' or 'expensive' depends on relevant comparisons to which the mind is anchored. The status quo often provides such a comparison standard. Consider the aftermath of hurricane Katrina. Authorities can allow residents to rebuild homes in the same manner as pre-Katrina, or alternatively introduce building codes requiring mitigation, or provide grants/ loans for residents to move to less risky areas. The status quo likely serves as a reference point to evaluate these alternatives. Anchoring can also produce framing effects when the starting point leads people to interpret values as gains or as losses. This then gives rise to the loss aversion bias described earlier.

09 Catastrophe Modelling

The use of catastrophe models for the estimation and pricing of catastrophe risk began in the 1980s with the improvement in computer systems and also the greater understanding of natural hazards. There are three major modelling firms that provide these models: AIR, RMS, and EQECAT. Although, at the beginning the insurance and reinsurance industries were sceptical about the use of catastrophe models, their use increased after hurricane Andrew in 1992 due to the usefulness of the models to predict the level of insured losses.

Unlike traditional approaches to actuarial/underwriter pricing which rely on historically observed data (e.g.: a burning cost approach) which is adjusted to reflect changes in portfolio over time; catastrophe models fit historical data over a much longer timescale (decades or centuries), and allow for changing frequencies of events over time, changing severity of impact of events, and changing the portfolio in a detailed manner which can be used to create possible future events which may have not happened historically. These allowances use latest research in seismology, meteorology, hydrodynamics, and can factor in the influence of building codes, construction types, engineering surveys, and loss mitigation. However, the use of catastrophe models has come under certain criticism in recent years. The increased reliance on these models coupled with the ever growing level of losses from catastrophes following the 9/11 attacks and hurricane Katrina in 2005 have led to calls from regulators and rating agencies for greater transparency and understanding of the assumptions used to build these models (Catastrophe Modelling Working Party, 2006; Financial Services Authority, 2006).

Though based on historical data, mathematical models, and the latest pertinent research, catastrophe models still carry with them a level of uncertainty which needs to be understood by their users. For one, when extreme events are modelled there are no prescribed ways to compute or elicit probabilities from different sources of information, nor for combining this information once probabilities have been established (Franklin, Sisson, Burgman, & Martin, 2008). (Re)insurers thus need to be aware that human judgments are part of the process of modelling extreme events. This is born out of necessity and not necessarily a bad thing. The point is simply to remember that there is also a degree of subjectivity embedded in the actual modelling process. A degree of uncertainty also arises from the way unknown parameters or missing data are handled. Often modellers can use a "default" or "unknown" option, and this is important for actuaries to be aware of in order to understand the basis for model predictions.

In order to understand the uncertainties inherent in modelling extreme events it is also important to consider the quality of the data that are the basis for catastrophe models. Catastrophe models rely on vast data points of variable quality for their estimates. Data for some geographic locations are more detailed and of better quality than for other geographic locations, and this contributes to more or less error in modelling outcomes. For example the data for predicting hurricanes in the USA are better than for Japan, due to the larger number of recent hurricanes in the USA, and also the more comprehensive understanding of locations within the USA.

Other considerations that are important when evaluating uncertainties inherent in catastrophe models include the frequencies used. Often models use long-term average frequencies for their predictions, however more recently large-scale events such as the 2005 hurricane season have shown that short-term and medium-term fluctuations need to also be taken into account. Different frequency distributions (Poisson or Negative Binomial) also have a different impact on the variability of losses. Modelling extreme events also usually implies using the tail (the extreme end) of distributions to model data. However, there can be considerable uncertainty about the shape of tails, especially when compared to other parameters such as the median or mean. Related to this, frequencies with higher return periods (1 in 100 years) are hard to back-validate, which again poses a significant challenge for catastrophe models.

It is obvious from the above discussion that a detailed quantitative understanding is needed to fully appreciate the model fitting and resulting confidence level that can be applied for a given portfolio.

Catastrophe models constitute the 'best bet' when it comes to extreme events such as natural disasters, but one cannot expect the models to be perfect. Uncertainties are part of the modelling process, and relatively small deviations from the model parameters can have a very large impact given the sheer scale of events when a major disaster strikes. Neither abandoning catastrophe models, nor a narrow interpretation of modelling outcomes appear to be ways in which to move forward. The ultimate challenge might then lie in the question how to supplement modelling outcomes with human judgments without falling prey to the various types of biases described in this report? With this in mind, the next section gives an overview of what we know about ways to reduce biases.

10 Intervention Techniques

COUNTERFACTUALS:

One way to reduce the use of heuristics when making decisions is to think of counterfactual scenarios. Thinking about converse and multiple alternative realities makes the decision process more systematic and less prone to suffering from heuristic thinking (Arkes, 1991; Galinsky & Moskowitz, 2000; Hirt & Markman, 1995; Hirt, Kardes, & Markman, 2004; Mussweiler, Strack, & Pfeiffer, 2000). Considering counterfactuals has been found to also improve decision making in groups by lowering the use of mental shortcuts (Kray & Galinsky, 2003).

INCENTIVES:

Other proposed de-biasing interventions have involved the use of incentives (promised future rewards) to improve decision making (Hsee, Zhang, & Chen, 2004; Stone & Ziebart, 1995). However, the results are mixed and rewards are not always successful at mitigating biases (Arkes, Dawes, & Christensen, 1986; Camerer & Hogarth, 1999; Hogarth, Gibbs, McKenzie, & Marquis, 1991).

TRAINING IN RULES:

Training in rules has also been found to ameliorate biases (Cheng, Holyoak, Nisbett, & Oliver, 1986; Fong & Nisbett, 1991; Larrick, Morgan, & Nisbett, 1990; Lehman & Nisbett, 1990; Nisbett, 1993). In these studies participants who underwent brief training in simple statistical rules were better able to overcome cognitive biases and arrive at better decisions. However, thus far there has been no evidence that rule-training would be successful at helping people use highly complex, unfamiliar, and abstract rules such as Bayes' rule (Larrick, 2004). A related finding relates to the way uncertainties are presented. In particular, there is ample evidence that presenting probabilities as frequencies makes it easier for people to understand probabilistic data (Gigerenzer & Hoffrage, 1995; Tversky & Kahneman, 1983). Thus, one way to de-bias people's decision making is to train people to convert probabilistic tasks into frequency formats (Sedlmeier, 1999).

GROUP DECISION MAKING:

Using groups for the decision making process has also been studied as a possible de-biasing intervention. Groups serve as error-checking systems, and increase the sample size of experience that is used to make a decision (Larrick, 2004). However, there are also pitfalls to using groups because social influence processes, as well as power or status relations can introduce a number of biases in decision making.

CONSIDERING ALTERNATIVES:

Other interventions aim to change the decision environment. For instance, when diagnosing a disease people make less biased judgements when different diagnostic scenarios are juxtaposed against each other rather than presented independently (Klayman & Brown, 1993). Similarly, asking people to list advantages and disadvantages of each treatment prior to making a decision for medical treatment ameliorated the use of heuristics (Almashat, Ayotte, Edelstein, & Margrett, 2008). In this regard it is interesting to note that some insurance companies are already using similar techniques for de-biasing decisions, such as, for example, peer review procedures or checklist monitoring.

INCREASING ACCOUNTABILITY:

Another de-biasing technique that has been used for the amelioration of heuristic thinking (in particular the availability heuristic) has been increased accountability, which is the requirement to justify one's judgements to others (Kennedy, 1993; Lerner & Tetlock, 1999; Simonson & Nye, 1992). However, this intervention has not always been found to be successful (Lerner & Tetlock, 1999; Siegel-Jacobs & Yates, 1996; Tetlock & Boettger, 1989), and some fallacies such as decision inertia can be enhanced when accountability is increased.

METACOGNITION:

More recently the concept of metacognition developed in the area of psychological educational theory (Flavell, 1979) has been applied to medical decision making (diagnostics). Metacognition refers to the ability of an individual to step aside from their thinking and observe it in order to recognise opportunities and needs for using intervention strategies. For example, in the context of medical decision making it has been suggested that educators should direct more effort at the specific cognitive requirements of clinical decision making (Croskerry, 2003a, b). For example, aids can be devised to minimise cognitive load in light of known limitations of human memory. Educators can also train people how to take multiple perspectives into account, as well as cultivate a capacity for reflection and self-criticism, by encouraging reappraisal of decisions in light of new information or input from other team members (see also Klein, 1998).

In sum, researchers have explored a number of de-biasing techniques. However, many are domain specific and their effectiveness in the insurance underwriting setting has yet to be established.

11 Conclusions and Unanswered Questions

This report aimed to review and summarise current literature on cognitive biases in catastrophe decision making. The report looked at six biases in particular: availability heuristic, small probabilities, temporal discounting, loss aversion, hindsight bias, and anchoring. It is important to note that there are many more cognitive biases that could play a role in (re)insurers' decision making in relation to catastrophe risks, however these were beyond the scope of the present report. The report also reviewed literature on catastrophe modelling, and suggested how cognitive biases may impact the interpretation of catastrophe models. Lastly, we reviewed de-biasing techniques that have been used thus far to ameliorate cognitive biases. Below, we integrate the knowledge gained from this review and suggest important questions that need to be answered in future research.

The paucity of research involving (re)insurance underwriters and brokers is an obvious shortfall in the current literature on risk decision making. Notwithstanding some notable exceptions, the majority of studies have focused on how individuals decide to purchase insurance for losses linked to natural disasters, in particular individuals who are directly affected. We know experts and lay people can differ in their risk perceptions, so it is important to also study the decision making processes of risk professionals such as underwriters or brokers. It also has to be said that much, although not all, of the evidence for biases in real-life settings appears to be anecdotal with researchers offering post-hoc explanations for a particular decision outcome. While informative, this kind of evidence is tentative and often leaves room for alternative interpretations.

One key question is how we can quantify heuristic thinking in domains such as catastrophe risks. Traditionally, heuristics capture deviations from decision outcomes that would be expected if decision makers were completely rational. Given the inherent difficulties in modelling extreme events such as catastrophes, it is unclear how one can establish objective criteria for reasoning about these events in the first place. This also makes it difficult to develop and evaluate intervention strategies to improve decision outcomes.

Related to the previous point, this report has highlighted several interventions used in different fields. However, the research is still in its infancy and calls for further testing in applied settings such as re/insurance underwriting, bearing in mind the aforementioned difficulties of establishing systematic human errors in the context of catastrophe risks. What is more, while systematic errors are well documented in other financial sectors (e.g., stock markets), little is known about the extent to which behavioural biases affect underwriting performance. The present report highlights the importance of behavioural factors when dealing with catastrophe risks. One next challenge ahead is to establish the full scale of the problem. Importantly, our review has highlighted the need for a combined approach that draws on mathematical catastrophe models as well as expert judgments to derive predictions of catastrophe risks. This not only raises the question how biases can be identified and counteracted, but also how precisely modelling outcomes and human judgments should be combined into an overall assessment. The industry would benefit from clearer guidelines if and how modelling outcomes should be adjusted to derive risk estimates.

In the long run one question is how to incorporate knowledge derived from behavioural science into business practices, and to develop tools and software applications that can assist decision makers in the re/insurance context (and indeed beyond). This is a herculean task; at present decision making tools that take into account behavioural biases are rare and at an early stage of development.

This report marks another important step towards closing the gap between academic and commercial expertise. However, global changes and increased exposure to natural disasters call for a closer partnership between scientists and the industry. The road from scientific advances to real-life applications is marked by uncertainty but a risk worth taking.

12 Glossary

Anchoring describes the process of using a starting point for evaluating or estimating unknown values.

Availability heuristic is the tendency for people to respond more strongly to risks when instances of those risks are more available to them, from memory, from imagination, from the media, from general social discourse or from their beliefs about the world.

Framing refers to the use of different schemas or standards to describe an event. The most widely studied frames are 'gains' and 'losses' because framing events in these terms often leads to different decision outcomes.

Gambler's fallacy is a tendency of decision makers to underestimate the probability of a repetition of an event that has just happened.

Hindsight Bias is the false belief that events are more predictable than they actually are.

Hyperbolic discounting is when discount rates in the more proximate future are steeper than discount rates in the distant future.

Loss aversion refers to the greater sensitivity of stakeholders to decreases, as opposed to increases in their wealth.

Mean-reversion bias is when decision makers assume that over time, a trend has to return to the mean.

Myopic loss aversion describes a phenomenon whereby investors are particularly concerned with the potential for a short term loss, even in the context of long-term investments.

Planning myopia is the tendency to consider consequences over a too restricted time horizon.

Reference points provide a comparison standard. For example, an investment can be construed as 'cheap' or 'expensive' depending on the relevant comparisons to which the mind is anchored.

Small probabilities refer to a group of biases that can arise when people reason about rare events. Small probabilities tend to receive too much, or too little weight depending on the decision context.

Status quo bias is the preference for things to stay the same.

Sunk cost bias arises when costs incurred in the past are used as a justification to continue investing in suboptimal projects or strategies in the future (in the hope to avert a large loss).

Temporal discounting refers to the fact that the greater the delay to a future reward, the lower its present, subjective value.

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14 Notes

Knowledge Transfer Network

Financial Services

THE LIGHTHILL RISK NETWORK