LLOYD'S

Emerging Risk Report 2017

Understanding risk

Reimagining history

Counterfactual risk analysis

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With expertise earned over centuries, Lloyd's is the foundation of the insurance industry and the future of it. Led by expert underwriters and brokers who cover more than 200 territories, the Lloyd's market develops the essential, complex and critical insurance needed to underwrite human progress.

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His broad experience in modelling has informed section 9, which he contributed.

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Background

All insurance professionals would benefit from a better understanding of risk. The objective of this report is to encourage insurers to think about risk in a different way by providing a systematic and in-depth framework for including downward counterfactual analysis in risk assessment.

Whenever an event occurs that takes the insurance market by surprise, questions are asked how the loss might have been averted or what additional risk mitigation measures might have reduced the loss. It is also useful for insurers and other interested parties to ask how the loss might have been worse. This is known as downward counterfactual analysis (upward counterfactual analysis considers what would have happened if things had been better).

Downward counterfactual analysis is rarely carried out and yet there is huge value in doing so. In statistical analysis, historical data is usually treated as fixed rather than one possible version of many that could have occurred if various influencing factors had been different.

This can be a weakness in risk modelling. For example, in the case of modelling rare extreme events the lack of loss data may give a false picture of the actual threat level, which could have been distorted by near misses and good fortune. Downward counterfactual analysis could help insurers to identify such anomalies, and to adjust risk models and pricing accordingly.

It can also help mitigate the inbuilt bias inherent in some risk models that are based on a single standard dataset. Although catastrophe risk modellers work independently of each other and take different views on many topics where risk ambiguity exists, there can be bias in the data if there are substantial common elements in the risk modelling for a particular peril.

Downward counterfactual analysis can provide insurers with the ability to search for and analyse data that may not be collected by historical real-world event research, and therefore can assist with the identification of unlikely but possible events (known as Black Swans).

About this report

Lloyd's, together with modelling company RMS, has published this report to provide insurers with a framework that helps enhance how they analyse risk.

We believe this is a useful addition to the suite of tools insurers and risk managers already use to analyse risk, including stress-testing techniques and statistical modelling, and could help them prepare business strategies, highlight potential vulnerabilities and make informed capital decisions.

The framework presented in the report can be applied to two distinct categories of risk quantification:

- Traditional probabilistic natural catastrophe modelling where counterfactual analysis can help validate models and insurers' understanding of systemic uncertainty. It also is a useful way of expanding stochastic datasets by analysing additional versions of actual events.

- Data-poor scenario-based modelling (especially for emerging risks), where counterfactual analysis could help create structured, transparent, scientific and evidence-led scenarios. These could augment existing limited historical loss event datasets and could improve insurers' assessments of probable maximum loss scenarios.

Systematic counterfactual analysis is rarely undertaken because of the substantial effort required, and because its purpose and value are underestimated. However, such effort would be rewarded by deeper risk insight for risk stakeholders, particularly insurers.

The framework is published in a mathematical appendix at the back of the report. Insurers can apply this to their scenario and loss catalogues.

Key benefits to insurers

Counterfactual analysis can benefit insurers in the following ways:

- Stretches the range of event possibilities in a plausible and scientific way
- Back-tests model results
- Mitigates bias in models that are based on the same datasets
- Explores the tail risks, and helps identify and thus prepare for Black Swan events
- Helps underwriters and risk managers analyse extreme and emerging risks
- Expands claims books and loss catalogues
- Helps facilitate complex explanation, deeper understanding and more coherent communication of future risks and modelling uncertainty to board members, policyholders, policymakers, risk managers and non-experts
- Provides a scientific and systematic approach to creating scenarios

For catastrophe risk quantification, counterfactual risk analysis can be applied in all three core catastrophe modelling activities of a P&C (re)insurer, namely pricing, capacity management and capital calibration.

This report shows how counterfactual analysis can be carried out in practice and acts as a starting point for further applied research into the value of counterfactual analysis for understanding historical events and their characteristics.

Box 1: Saved by 30 metres – an aviation near-miss

On the evening of 7 July 2017 Air Canada flight AC759 from Toronto was preparing to land at San Francisco airport. As the weather was clear, the pilot was on a visual approach but failed to see he was guiding his plane towards a taxiway on which there were four fully loaded planes waiting for take-off.

Air traffic control ordered the AC759 to abort the landing when the aircraft was just 30 metres off the ground. Event reconstruction showed that had the AC759 pilot pulled up five seconds later he would have hit the third plane on the taxiway (Mercury News, 2017).

30 metres was the difference between no accident taking place and what could have been the greatest aviation disaster in history involving multiple planes and more than 500 passengers. The FAA/NTSB launched an investigation.

Applying downward counterfactual analysis in a reasonable and scientific way to this event could help the insurance industry understand the potential total economic loss and insurable losses from a catastrophic event on a scale of the one that almost took place. It would also help insurers create an alternative claims book, which would offer a view of plausible losses that could have impacted their business.

1. Introduction

Whenever an event occurs that takes the insurance market by surprise, questions are asked how the loss might have been averted, or what additional risk mitigation measures might have reduced the loss. It is also useful for questions to be asked how the loss might have been worse. To analyse what could have happened if events had turned for the worse is called a downward counterfactual. By contrast, an upward counterfactual considers what could have happened if events turned out better.

Psychologists of counterfactual thinking (Roese, 1997) observe that upward counterfactual thoughts are much more common than downward ones. Upward counterfactual thoughts can encourage positive changes in behaviour. If a student has failed an exam, they might have the upward counterfactual thought that if only they had studied more diligently, they might have got better results. All insurance professionals wish to have a better understanding of risk. To this end, the objective of this report is to encourage more systematic and profound downward counterfactual thinking in all lines of insurance. This encouragement is needed, because this kind of thinking goes against the grain of human nature. Counterfactual disaster risk analysis is rooted in fundamental concepts as basic as claims analysis, yet this is a subject absent from professional insurance education or training.

Downward counterfactual thinking is a mode of lateral thinking (DeBono, 1977) that changes the focus and breaks free from the limits of traditional thinking. Unusual thinking is needed to avoid surprises. As a salient illustration of the power of downward counterfactual thinking, consider 9/11, the epitome of a Black Swan event (Taleb, 2007). This terrorist attack spawned numerous upward counterfactual thoughts: if only the FBI had the legal authority to open the computer of a terrorist suspect; if only the FBI and CIA shared intelligence more widely; if only security at Boston's Logan airport had been tighter. A natural upward counterfactual question that was regularly asked is: 'Why did this happen?' The less natural but more searching downward counterfactual question following 9/11 is: 'Why didn't this happen before?'

Less than two years before 9/11, on 31 October 1999, an Egyptian pilot deliberately crashed EgyptAir 990 into the Atlantic en route from JFK to Cairo (Joscelyn, 2016). As observed by his aide-de-camp, Nasir Al Wuhayshi, Osama bin Laden himself had the downward counterfactual thought that if a passenger jet leaving JFK could be ditched into the sea through malicious pilot action, it could also be flown into buildings (Joscelyn, 2016). Risk analysts would benefit from thinking counterfactually.

Substituting New York for Paris, a deliberate terrorist plane crash into an iconic Western structure almost happened six years earlier, when terrorists hijacked AF8969 in Algiers on 24 December 1994. Fortunately, the French authorities had an informant within the GIA Algerian terrorist organisation. Warned of the true intent of the hijackers to crash the plane into the Eiffel Tower, the French authorities despatched commandos to storm the plane whilst it was refuelling in Marseilles (Hoffman and Reinares, 2014).

Most events have either happened previously, almost happened previously or might have happened previously. Conceptually, the historical past has a dense labyrinthine event-tree structure, and the domain of future possibility is mostly spanned by history, its perturbations and variants. Yet, the past is typically perceived in a fatalistic way somehow as having been inevitable. The term for writing of alternative realisations of the past in the English language is "counterfactual history". This expression does not exist in other European languages (e.g. German, Italian, Spanish, French, Greek, Icelandic etc), in which the same word is used for history and story. For native speakers of such languages, including insurance professionals, contemplating other versions of history would have to overcome an obstacle of vocabulary; the idea of a counterfactual narrative may seem self-contradictory.

In January 2015, an Italian pilot texted his wife threatening to crash his passenger jet if she left him (Chan, 2016). The woman immediately told police who alerted officials at Fiumicino Airport in Rome. The pilot was suspended from duty shortly before he was due to fly to Japan. The timing of this incident is particularly salient, because only two months later, on 24 March 2015, Andreas Lubitz a Lufthansa pilot who was diagnosed with mental health problems crashed Germanwings Flight 9525 into a French mountainside killing all 150 on board (Willsher, 2016). Counterfactually, had the Italian episode been publicised, the mental fitness of pilots might have come under closer scrutiny earlier.

Counterfactual risk analysis plugs a longstanding gap in the science of risk modelling. Constructing event sets for a catastrophe model is essentially a forward linear process. Starting from a large ensemble of hazard events, catastrophe modellers assess the damage implications of each scenario, and then calculate the consequent insured loss. Extensive analysis of historical events provides the empirical foundation of both actuarial analysis and catastrophe risk assessment. However, there is no explicit systematic reverse search in time for downward counterfactuals corresponding to potential Black Swans.

Disaster science tends to make stepwise jumps in the wake of disasters. Post-event engineering reconnaissance missions survey damage in fine detail. The purpose is to understand as best as possible what actually happened. Comparatively little attention is given to what *might* have happened. Faster progress in disaster science might be made through a systematic and thorough assessment of downward counterfactuals. This is by itself a demanding technical undertaking, and so has never been a core objective or priority of catastrophe risk analysis. This is reflected in the absence of counterfactual vocabulary in the literature on catastrophe modelling. Some stress tests devised for catastrophe model sensitivity analysis such as increasing event frequencies may constitute downward counterfactuals, but the broader domain of downward counterfactuals is not explored.

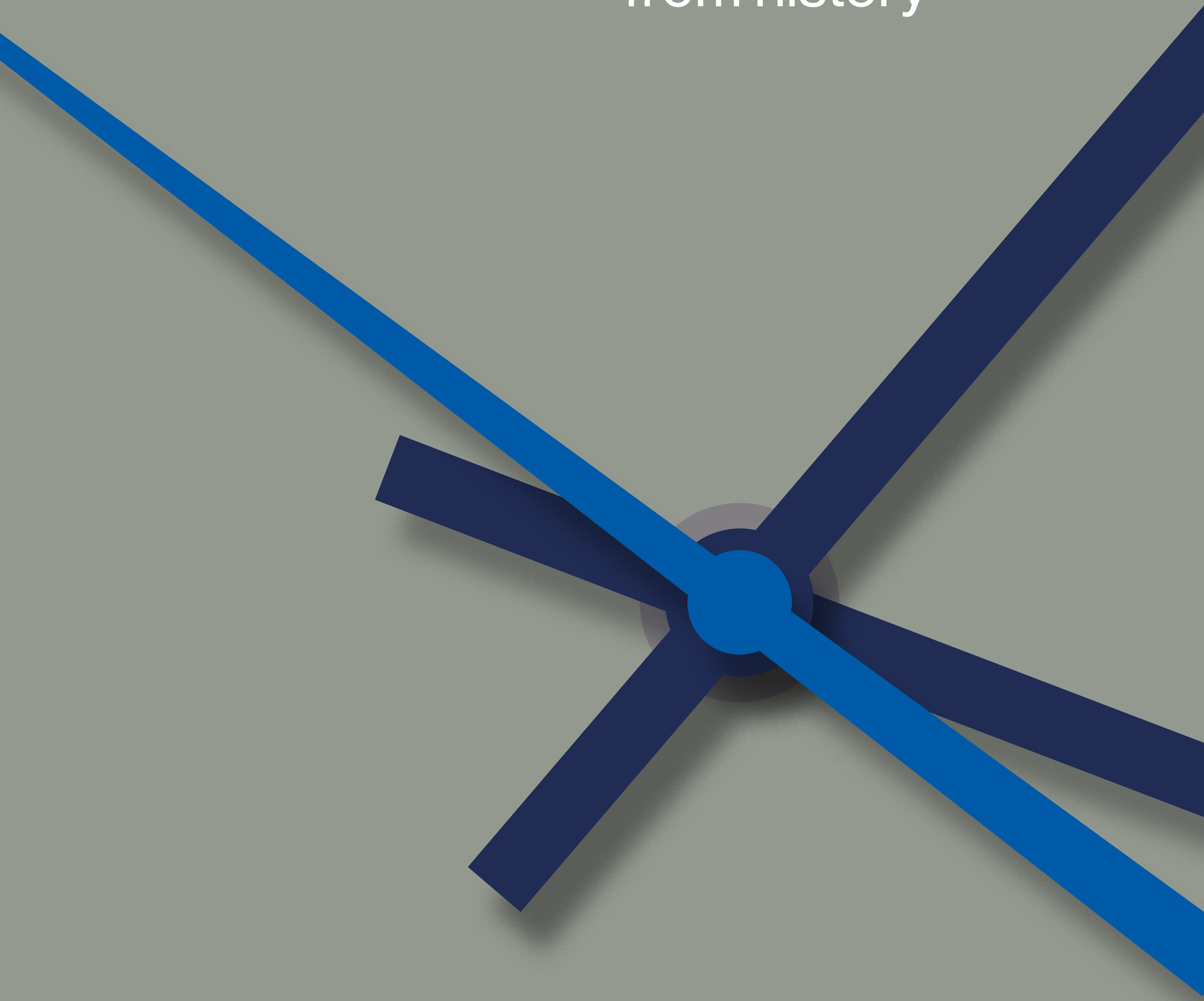
Due to the finite size and resolution of catastrophe models, restricted by practical run-time constraints of a few hours, it is inevitable that some significant downward counterfactuals may not be found as scenarios in any catastrophe model. Counterfactual risk analysis can help identify these unknown or poorly recognised sources of unmodelled risk, and gauge their contribution to key insurance risk metrics. Furthermore, even where significant downward counterfactuals are already represented as catastrophe model scenarios, these can be usefully benchmarked against counterfactual risk analysis.

In statistical analysis, the past is traditionally treated as fixed, rather than just one possible realisation of what could have transpired. For rare extreme events, the sparse and incomplete historical catalogue may belie the actual threat level, which may be overshadowed by near misses and masked by good fortune. Through adopting a counterfactual perspective on historical experience, exploring other possible realisations of history, additional insight can be gained by insurers into rare extreme losses that might otherwise come as a surprise or business shock.

In political science, counterfactual thinking is necessary for drawing causal inferences from historical data (Tetlock et al., 1996). These inferences are of value to political risk underwriters. Here are two terrorism examples to illustrate how counterfactual risk analysis can make catastrophe modelling more robust. A year after the Baltic Exchange London vehicle bombing by the IRA in 1992, Pool Reinsurance Company Ltd. was established. Suppose that UK terrorism risk modelling had been instigated around that time, rather than after 9/11. Vehicle bombs would have constituted the primary attack mode scenarios modelled. But a counterfactual analysis of the 1994 GIA hijacking would have motivated scenarios for aircraft impact into iconic buildings, even though the Eiffel Tower survived the GIA plot (Jenkins P., 2003). This is indeed a realistic terrorist attack scenario. Although there has yet to be a successful terrorist aircraft attack on an iconic UK building, in 2003 terrorists planned to hijack a plane at Heathrow, stun the crew, and fly the plane into the Canada Tower in London's Docklands financial district (DHS, 2006). Plot details were found on a computer of an Al Qaeda operative seized in Lahore. Furthermore, the Al Qaeda training manual includes a specific threat against Big Ben, the iconic clock tower at Westminster (Jenkins B., 2006).

Similarly, as a second example, suppose that US terrorism risk modelling had begun after the World Trade Center bomb attack on 26 February 1993. Counterfactually, the Egyptair pilot suicide flight from New York to Cairo on 31 October 1999 could have struck a New York skyscraper. Accordingly, even before 9/11, this scenario, (which the CIA had themselves imagined), should have been included in any US terrorism risk model. Inclusion of such a scenario would have led to assessment of the damage caused to a skyscraper from a passenger jet impact, and the exploration of numerous secondary insurance losses. Crucially, this scenario would have exceeded the engineering design basis for external impact and subsequent fire. A lesson from 9/11 is that the search for downward counterfactuals can reveal hitherto unknown tipping points of catastrophic loss.

Learning more from history



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2. Learning more from history

Disasters occur over the passage of time, and the historical record is the fundamental data resource available. For any peril, catastrophe risk analysis is an observational discipline where significant progress can be anticipated as and when major events occur. But laboratory experiments are only possible on a small scale. The maximum knowledge benefit must be gained from historical experience. This includes not just what happened, but also what almost happened and what might have happened.

With earthquake engineering design levels for structures expressed in terms of return periods of hundreds and even thousands of years, seismic hazard analysts need to glean as much information as possible from historical earthquake catalogues, and their extension further backwards into archaeological and geological time. Progress in seismic hazard analysis has been advanced notably by learning more from the evidence of the past.

The timescales for other geological perils, such as tsunamis and volcanic activity, can be as protracted as for large earthquakes. Accordingly, volcano hazard analysts seek to maximise the information content gained from study of the past. In 1994, the second edition of the Smithsonian Institution compendium on volcanoes of the world was published (Simkin et al., 1994). This standard international reference on volcanic activity had only one entry for the Soufrière Hills volcano on the Caribbean island of Montserrat, namely the 1630 eruption. The eruption the following year in 1995 came as a widespread surprise to many stakeholders, not least insurers - the volcano had been thought to be effectively dormant. The 1995 eruption and ensuing volcanic activity caused substantial economic loss to the island of Montserrat.

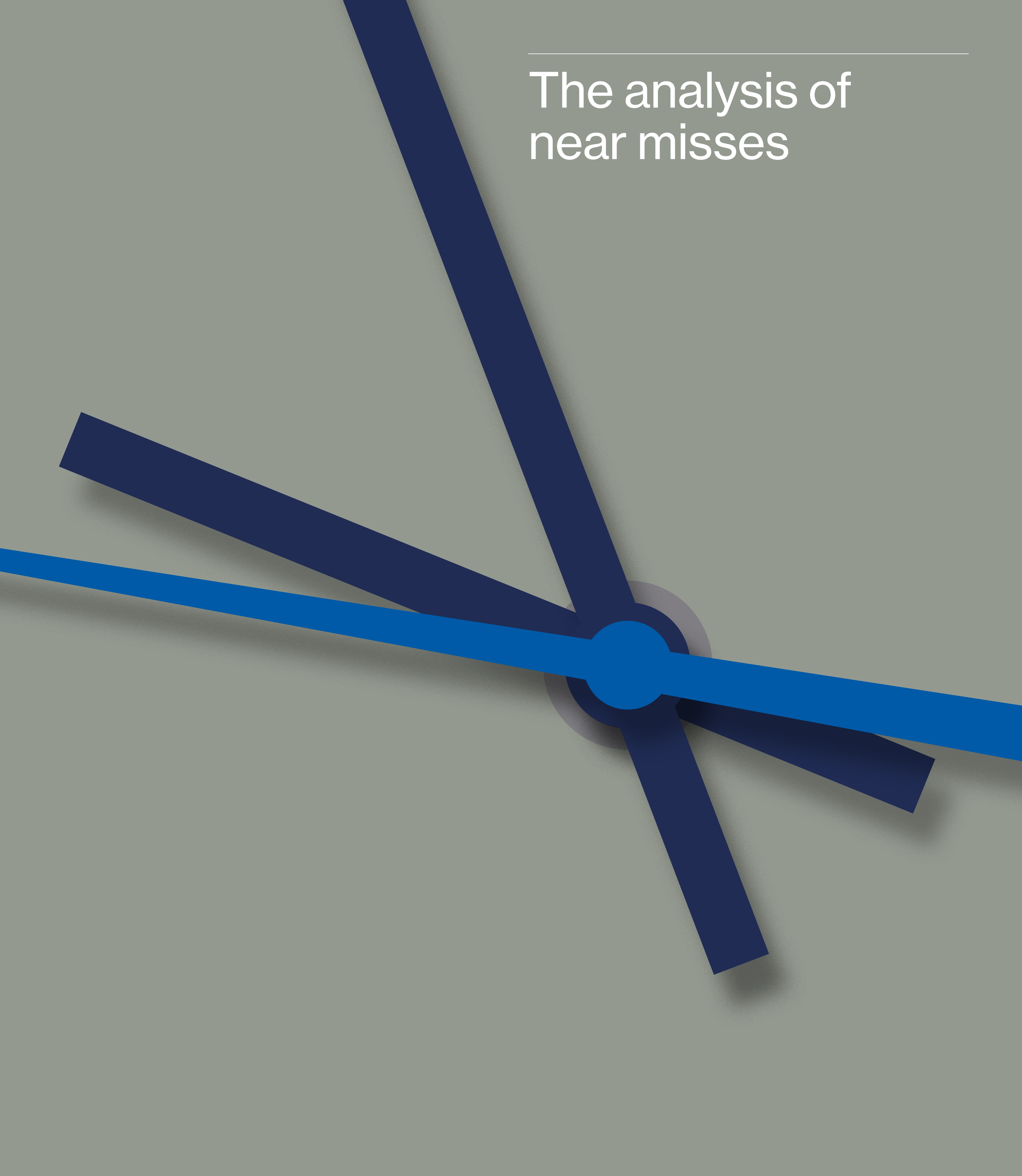
Yet, there had been three well-documented periods of notable unrest on the Soufrière Hills volcano in the 1890s, 1930s and 1960s. Counterfactually, these unrest periods might have led to an eruption. The 1930s unrest was marked by sporadic bursts of seismic activity, which led up to a M6.2 earthquake on 10 November 1935 (Powell, 1938). This sizeable earthquake might potentially have triggered an eruption. As it turned out, seismicity levels decayed afterwards. Remarkably, the spatial pattern of earthquake epicentres has some striking similarities with that at the start of the 1995 eruption. For the third of the unrest periods prior to 1995, seismologists concluded that there was an abnormally high risk of an eruption in the near future. Probabilistic volcano hazard assessment should not be based solely on actual past eruptions, which may be a very sparse dataset, but should take proper counterfactual account of the periods of unrest, which constitute a vital element of the knowledge of the activity status of a volcano.

Lessons learned from disasters often come after catastrophic economic losses. Consider merchant shipping, and the commercial pressures to arrive on time in port. Because the time window for arrival may be restricted by tides, a moderate delay in arrival could lead to large schedule disruption. Some transportation disasters have arisen because of action taken to maintain schedule. For example, the 2005 Amagasaki rail crash in Japan killed 106, including the speeding train driver (McCurry, 2005). For a ship's captain or train driver, the reward of keeping to schedule may justify taking some extra risks.

In October 2011, New Zealand's worst maritime pollution disaster occurred when the cargo ship *Rena* ran aground in the Bay of Plenty, North island of New Zealand. Hundreds of tons of oil leaked into a pristine area. Crucially for risk management, *Rena* hit a reef when the vessel cut corners trying to get to port quickly to make up time (TAIC, 2014). Marine insurers who sought a precedent had to look no further than the first oil tanker environmental disaster.

The *Torrey Canyon* tanker, heading for the Welsh port of Milford Haven in March 1967, changed course to pass through the Scilly Isles to make high water at the port, and save a five-day delay (Professional Mariner, 2007). What should have been a safe passage proved catastrophic when the captain was unable to make his desired turn because of fishing boats. The tanker foundered on rocks and 100,000 tonnes of oil polluted the English Channel coastline. Numerous upward counterfactuals were considered: if only the captain had chosen a different route through the Scilly Isles; if only the fishing boats had not been out; if only the captain had not forgotten to put the helm on manual. However, many downward counterfactual questions could also have been asked to perturb the event by modifying its affecting variables in a scientifically plausible and reasonable way.

Saving of time is not the only reason a captain might cut corners and depart from the scheduled route. On 13 January 2012, the Italian cruise ship Costa Concordia was wrecked off the Italian island of Giglio. The captain had deliberately taken the ship off its scheduled course to sail as near the island as the coastal safety contour would allow, to give his passengers a close view of the island and for the islanders to greet the passengers (NBC News, 2014). The Indonesian helmsman might have averted the disaster but did not comprehend the captain's order to change course before the ship foundered; sailing on the island's safety contour was a risky tradition. Far from occurring out-of-the-blue as a surprise, this disaster could well have happened before. But it would only have emerged through downward counterfactual interrogation of historical shipping routes. Given today's technology and the ability to have access to real-time ship positions, marine traffic and route history (e.g. Windward, FleetMon, MarineTraffic, Pole Star and others) this kind of investigation would have been possible but it would have still required a substantial effort that is seldom made for near misses.



The analysis of near misses

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3. The analysis of near misses

The concept of a near miss is familiar to all in a general colloquial sense, but the formal analysis of near misses to gain insurance insight is not widely known or appreciated. There is a psychological dimension to the human perception of near misses. In lotteries and gambling games, narrowly missing a jackpot incentivises the player to carry on playing. Correspondingly, the occurrence of near misses has been deliberately inflated in casinos (Reid, 1986). In matters of chance, where the jackpot is associated with a major loss rather than huge win, near misses can have a different effect on human behaviour. Some may be reassured that luck is with them or that providence has guided them; others would be relieved to have avoided a major loss and be glad to move on. Few would be motivated to examine, let alone quantify, the reasons for their good fortune.

Where insurance claims data are abundant, statistical analysis of accident information suffices for insurance purposes, without the need to collect or assess near miss events as well. Consider auto accidents. Near miss accidents are commonplace, but for most types of auto accident, there are enough loss statistics for near misses to be ignored. However, for unusual catastrophic auto accidents supplementary information would be insightful. One of the most extreme UK auto reinsurance claims arose with the Selby rail crash in February 2001, when a car veered off a motorway onto a railway track. The car was then struck by a train, which partially derailed and struck another train, with fatal consequences. The auto liability losses amounted to £30 million from a single insurance policy (MacMahon, 2011), Statistics on cars halted on railway tracks, for whatever reason, would be relevant to review for risk assessment purposes.

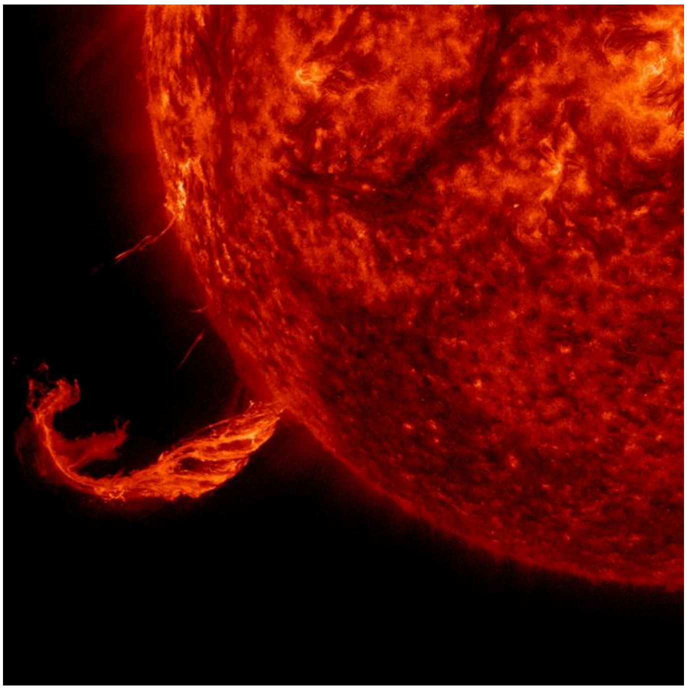
The tail of the counterfactual loss exceedance probability distribution for a historical event can be explored in considerable detail. This is valuable for sense-checking because of its linkage with catastrophe modelling output. As an example, consider Hurricane Ivan in September 2004. Almost a year before Hurricane Katrina devastated the Gulf Coast, Hurricane Ivan, a category 4 hurricane with 140 mph winds, was slowly moving directly toward New Orleans.

Fortunately for New Orleans, the storm veered to the north and made landfall east of Mobile Bay, Alabama. But forecasters at one stage were predicting a 25% probability that Ivan would remain on track to strike New Orleans as an extreme storm. Stochastic modelling of Hurricane Ivan, at that stage heading for New Orleans, would have an event tree for: (a) the track geometry; (b) the hurricane category on landfall; (c) the height of the storm surge; and (d) the consequent inland flood potential. In the tail of the counterfactual loss distribution for Hurricane Ivan would have been a loss actually realised the following year with Hurricane Katrina. This pattern was repeated a few years later in August 2011 when Hurricane Irene was a near-miss disaster for New York. The potential for catastrophic loss in the New York area from a severe hurricane was realised the following year with Superstorm Sandy. Downtown subway stations were flooded that narrowly missed flooding the previous year.

There are numerous perils for which extreme dangerous events are thankfully rare. The sparsity of actual loss data then presents a challenge for insurance pricing and risk management. Understanding of the underlying risk can be greatly enhanced by analysis of near misses. Minimal historical loss is often perceived as an indication that the risk is minimal. Absence of loss is often misinterpreted as absence of risk. Absence of evidence is not to be confused as evidence of absence. There are many examples from natural and man-made hazards that could be cited to highlight the value of near miss analysis.

A natural, but extra-terrestrial, hazard is first considered: a Coronal Mass Ejection (CME) from the sun. The largest historical solar storm occurred in 1859 and is known as the Carrington event, named after the English astronomer who documented it in detail. On 23-24 July 2012, a Carrington-like event occurred, but fortunately the Earth was not in the line of impact of the solar storm. But nine days earlier, the ignition spot of the CMEs had been pointed directly at the Earth (NASA, 2012). Given that the regions of the sun near its equator rotate every 25 days, the counterfactual chance of a Carrington-like event in July 2012 was about 4%. Historical near misses such as this should be taken into account in solar storm hazard analysis. The opening ceremony of the 2012 London Olympics was on 27 July 2012. The commercial success of these Olympics would have been marred by solar storm disruption of satellite communications. Lloyd’s has been exploring space weather and solar storms risks since 2010 in two reports. ‘Space weather: its impact on Earth and implications for business’ (Lloyd’s and RAL Space, 2010) and ‘Solar Storm Risk to the North American Electric Grid’ (Lloyd’s and AER, 2013). In the latest report Lloyd’s estimated that the total US population at risk of extended power outage from a Carrington-level storm is between 20-40 million, with durations of 16 days to 1-2 years (depending on spare replacement transformers). The total economic cost for such a scenario is estimated at US$0.6-2.6 trillion. In the Lloyd’s City Risk Index 2015-2025, the combined average GDP@Risk over 10 years at risk from solar storm for 301 cities is US$ 64.95 billion[i] with Tokyo, New York, Moscow, Los Angeles and Paris in the top five.

If major near miss events are rare, as with solar storms, and the chance of a near miss becoming a hit is sufficiently small, then many years may pass before a disaster materialises. Consider a specific notable case: the Columbia Shuttle disaster. On 16 January 2003, during the launch of Columbia's 28th mission, a piece of foam insulation broke off from the Space Shuttle external tank and struck the left wing of the orbiter (Howell, 2013). On re-entry, hot atmospheric gases destroyed the internal wing structure, with fatal consequences. From 1981 until the accident, foam loss occurred on more than 80% of the shuttle missions for which imagery was available. In addition, serious foam loss occurred in almost 10% of the observable cases (CAIB, 2003). Combining the probability of critical damage from serious foam loss with the incidence frequency would have yielded the probability of mission failure. But such a quantitative risk assessment would have required a substantial degree of analytical effort that is seldom made for near misses.

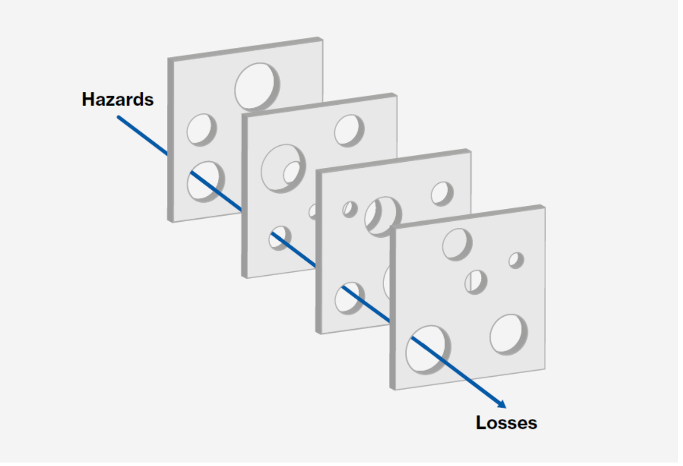


Source: NASA Goddard Space Flight Center (2015)

[i] Note that the GDP@Risk is a 10 year average allowing for the probability of occurrence of a hazard. Given that most risks are extreme but very unlikely the true cost of any major event is likely to significantly exceed the average. The GDP@Risk is a “savings rate” which shows approximately how much money should be set aside over the period to pay for the expected losses in the long run.

Defence-in-depth is key to making engineering systems robust. One line of defence may fail, a second also may be breached, even a third. But if there are multiple layers of defence, then the only loss mechanisms are those that circumvent them all. If most fail, but not all, a near miss is registered. The engineering principle of defence-in-depth can be graphically represented as a series of barriers with sporadic holes, somewhat resembling Emmenthal cheese. The 1997 version of James Reason's Swiss Cheese Model involved a succession of defensive layers, including a variety of barriers and safeguards. Only when a series of holes line up can an accident trajectory pass through the defences to cause harm. The holes arise from unsafe acts and latent conditions associated with failings of designers, builders, managers and operators. The Selby rail crash might have been averted had there been better motorway crash barriers to prevent cars from veering onto a railway track. Corporate safety culture affects all parts of a system. The 2010 Deepwater Horizon oil platform fire and explosion and Gulf Coast pollution disaster resulted from a breach of no less than eight defensive barriers (Woo, 2011). Latent conditions involving human error eroded their independence, inducing an implicit degree of correlation and systemic risk.

Figure 1: James Reason's Swiss Cheese Model



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If things had turned for the worse

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4. If things had turned for the worse

The International Atomic Energy Agency (IAEA) plays an important global role in ensuring high standards of nuclear safety throughout the world. IAEA undertook a detailed study of the M6.8 Japanese earthquake of 16 July 2007, which caused the seismic ground motion at the nearby Kashiwazaki-Kariwa nuclear power station to exceed the design basis significantly (IAEA, 2007). Notwithstanding this surprisingly high earthquake loading, due to the conservatisms introduced at different stages of the design process, the plant managed to operate in a safe manner, during and after the earthquake.

This earthquake placed under scrutiny the seismic design basis of Japanese nuclear plants. International concerns over the design basis were realised a few years later with the Fukushima accident on 11 March 2011. The causative M9 earthquake generated a massive tsunami that overtopped the plant tsunami protection. The maximum credible earthquake had been thought to be only M8.2 (Ruff and Kanamori, 1980). The significant underestimate of the maximum possible tsunami height led to the release of radioactivity from the Fukushima nuclear plant. Counterfactually, the disaster might have been worse. From RMS examination of wind data around Fukushima, there was a significant chance of the wind direction blowing inland, causing more widespread radiation contamination. Fortunately, the wind blew most of the radioactivity released from the stricken nuclear plant out to sea.

In a short story of counterfactual fiction, Fritz Leiber (2010) recounts the intent of a professor of social history to entitle his master work either, *'If things had gone wrong'*, or, *'If things had turned for the worse'*. Especially with new technologies like drones, which have come close to causing civil aviation disasters (Davies, 2017), such a downward counterfactual work would be insightful. Taking the proximity of a drone to a plane as a severity measure, statistics of near misses can be extrapolated to estimate the likelihood of a collision.

In the aftermath of major events, intensive industry reconnaissance is conducted to investigate as thoroughly as possible what actually happened. However, post-event analysis is labour-intensive and time-consuming, and resources are rarely allocated to venture further and explore downward counterfactual, hypothetical, questions. Attention is especially merited for those downward counterfactual scenarios, such as an unfavourable wind direction, that were at least as likely as the actual historical event.

If losses are severe, counterfactual questions are often asked as to what factors exacerbated the losses, and how future losses might be mitigated through enhanced safety and security measures, better land use planning etc. Major conflagrations and explosions may be due to accidental causes, which merit investigation. However, if actual losses have been light or not severe, counterfactual questions are less likely to be investigated.

There is an inherent outcome bias in reviewing losses. As Kahneman (2011) has pointed out, decisions tend to be judged according to the outcome. In the case of (re)insurance, favourable underwriting results do not trigger the same level of post-mortem analysis as a severe and unexpected underwriting loss. Furthermore, little compels management to conduct a root-cause analysis of near misses that could have been catastrophic had environmental conditions been slightly different. Where outcome bias is prevalent, the quality of capital management decisions and indeed wider risk governance decisions may potentially be deficient and exposed to unpleasant surprises. There are many lessons to be learned in risk awareness and catastrophe risk management from asking downward counterfactual questions about historical events - not just extreme events, but also those that might be classified as near misses.

What dynamic perturbation might have transitioned a system to a state of much greater loss? How likely was such a perturbation? What might the direct losses have been? How large might the indirect economic losses have been? The risks of behavioural biases in risk thinking along with methods to mitigate them were highlighted in Lloyd's reports Cognition: Minding Risks (2012) and Behaviour: Bear, Bull or Lemming (2010).

Tidal change constitutes such a perturbation for storm surge risk. During the blizzard of February 2013, a four-foot storm surge hit Boston at low tide, not high tide. With the high tide already a foot higher than average because of the new moon, coincidence of the storm surge with this high tide would have given rise to the 100-year flood (Conti, 2015). In this example, the chance of such coincidence with the high tide was approximately 1/6. As with a dice throw, the odds favoured insurers.

Sometimes the odds are stacked against insurers but they get a lucky break. In order not to be fooled by randomness (Taleb, 2001), insurers should appreciate how luck has mitigated their losses, and what might have happened if things had turned for the worse. On 16 January 2013, Jihadis attacked the In Amenas gas plant in Algeria, operated by Statoil. The plant could have been blown up but for a bullet that cut the plant power supply and shut down operations (Statoil, 2013). The terrorists' objective was to restart the factory and explode it (Nossiter and Kulish, 2013). Counterfactually, the gas plant could have been destroyed.

Without a good amount of luck, things might have turned for the worse for insurers during the Easter 2015 jewellery heist in Hatton Garden, London, the biggest in British legal history (BBC, 2016). The size of this record jewellery haul could have been more than 10 times greater if a hydraulic pump had not broken during the forced entry into the vault. This unforeseen mechanical failure caused two of the gang to quit, and halved the time available for rifling through the many safety-deposit boxes stored in the vault.

In the February 2016 SWIFT cyber-attack on the Bank of Bangladesh, US$101 million was stolen. But it could have lost another US$850 million but for the word 'Jupiter'. Hackers broke into the bank computers and sent out payment orders for US$951 million to the Federal Reserve Bank of New York. It paid out US$101 million before its security systems noted that one of the payments was going to a bank on Jupiter Street in the Philippines. The word Jupiter triggered a payment refusal because the name was also that of an oil tanker on the Fed's Iran sanctions watch-list (Das and Spicer, 2016). Counterfactually, investigating and recoding in an alternative loss book an event that could have been almost a US$ 1billion could allow insurers to analyse extreme losses and understand the impact it might have had on the business. As it turned out, the actual loss was reduced further by US$20 million by another accident: a spelling error in the payment request.

With Iranian sanctions lifted in January 2016, international oil exports from Iran resumed. The Singapore Strait is one of the world's busiest shipping routes. There, on 3 August 2016, a 320,000 ton Iranian oil tanker *Dream II*, owned by Iran's leading oil tanker operator NITC, collided with a 14,000 container ship *Alexandra* (The Marine Executive, 2016). The tanker's bow hit the *Alexandra*'s port quarter resulting in significant damage to its hull. Ten empty containers on board the *Alexandra* fell overboard, five of which landed on the deck of the *Dream II*. Before the collision, the Port Operations Control Centre of the Singapore Maritime Port Authority provided traffic information and alerted the shipmasters of *Dream II* and *Alexandra* of the risk of collision. Both vessels remained stable and safely anchored in Singapore. The incident fortunately caused no injuries or major oil pollution, but it is one of the first examples of sea collisions between mega vessels.

Inexperience on the bridge of the *Dream II* and lack of modern collision avoidance technology contributed to the accident. How could things have turned for the worse? Lateral downward counterfactual thinking can substitute intent, capability and opportunity to make things worse. Although the collision was accidental, counterfactually, the ramming of the *Alexandra* might have been intentional. A malicious maritime accident has been a Singapore counter-terrorism concern since 9/11 (NSCS, 2004). After rogue truck drivers and airline pilots, the idea of a rogue ship captain has to be treated as credible. Furthermore, a more damaging collision could have resulted if there had been some cyber hacking that might have affected navigation systems. As operations become increasingly internet-enabled, this is a growing maritime concern.

An important knowledge gain from downward counterfactual thinking comes from exploring the loss potential if things had turned for the worse.

Suppose there had been a full collision, causing an oil leak from *Dream II*. Assessment of the international coastal pollution implications for this hypothetical scenario requires a quantitative environmental impact analysis with a fine degree of geographical resolution. Whilst such environmental impact analyses are not feasible for large numbers of future collision scenarios, it is practical to conduct such studies for a few salient historical collisions or near miss events.

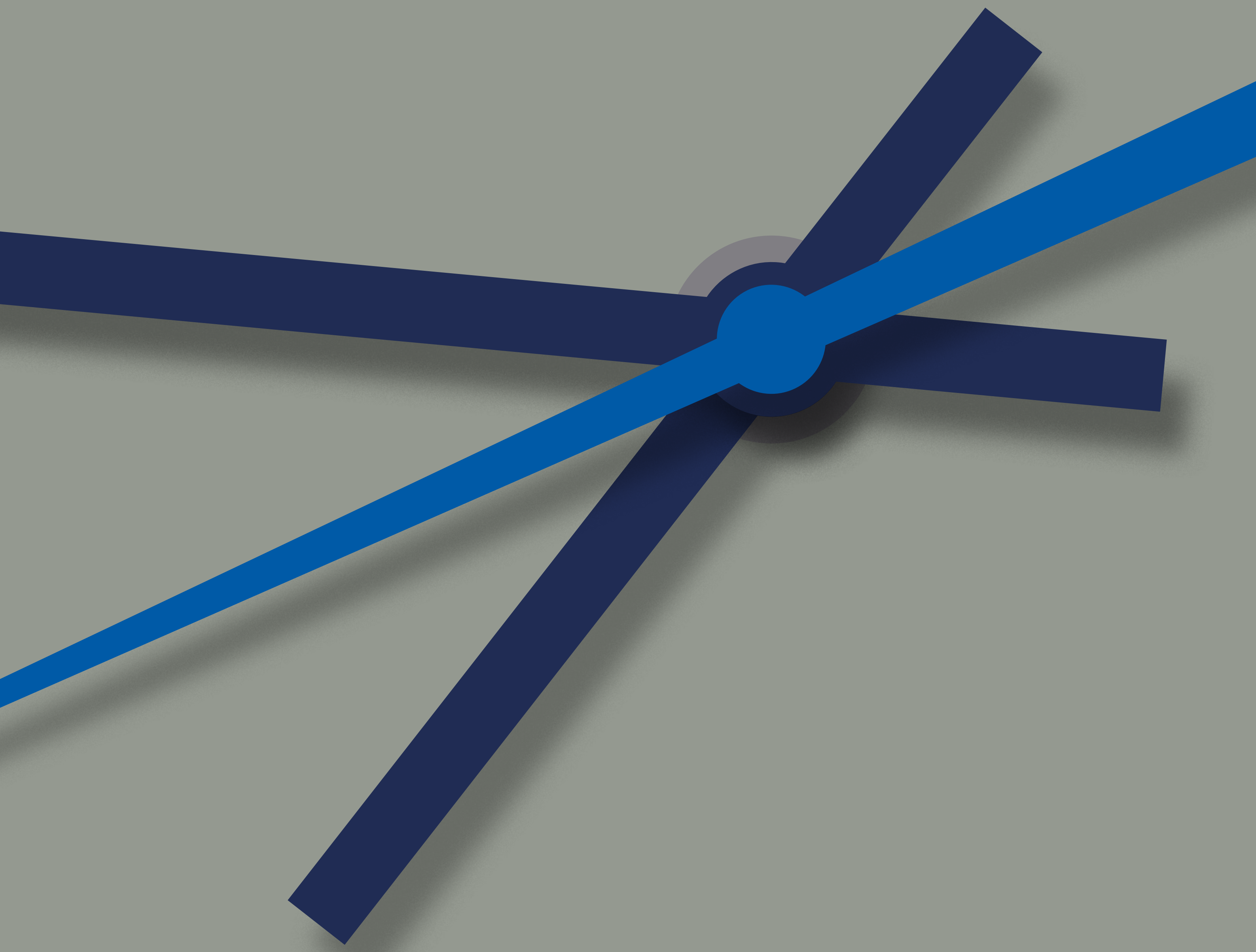
Disasters are complex phenomena that may be compounded from a variety of aggravating external factors. In the case above, poor visibility due to bad weather would increase the chance of ship collisions. Strong winds are an aggravating hazard at sea, and also on land in respect of fire following earthquake and wildfire. The worst US historical wildfire was the Oakland Hills fire of October 1991, which killed 25 people, injured 150 and destroyed more than 3,800 homes (Parker, 1992). A number of factors created the opportunity for disaster. When the Santa Ana wind condition was added, the combination was more than any fire department could handle. The fire was out of control and was contained only when the wind changed. Sensitivity to the wind direction was also a feature of the May 2016 Alberta wildfire. Ten percent of Fort McMurray was destroyed by fire, but the loss would have been far greater if the hot dry weather had persisted and the wind direction had changed. The chance of the wind blowing towards northern industrial facilities can be estimated from local wind data (Weather Stats, 2017).

The spread of wildfire has some similarities with the spread of infectious disease. Both can grow exponentially if no effective containment controls are in place. An alarming human health disaster emerged in West Africa in 2014 with the Ebola epidemic. Eventually, after months of spreading with limited influence by the medical services and public authorities, and meagre international funding, the Ebola epidemic was finally brought under control. But this epidemiological containment would have been almost impossible if a civil war had been raging in West Africa at the time. Both Sierra Leone and Liberia have been prone to sustained political violence. Indeed, for half of the past 25 years, there has been civil war in one of these countries (Annan, 2014). Counterfactually, had there been a civil war in either country in 2014, for which there was a 50% chance, the authority to enforce quarantines and safe burial practices would have been greatly diminished, and the Ebola epidemic would have been very hard to bring under control.

A different example is MERS, a viral respiratory disease caused by a novel coronavirus (MERS-CoV) that was first identified in Saudi Arabia in 2012. Approximately one-third of reported patients with MERS have died. Although most human cases of MERS have been attributed to human-to-human infections, camels are likely to be a major reservoir host for MERS-CoV and an animal source of MERS infection in humans. The virus does not yet pass easily from person to person unless there is close contact. However, a far more transmissible mutation of MERS could emerge and there is still no vaccine or specific treatment for MERS available. So the emergence of a readily transmissible mutation of MERS, (called MERS+), would have severe implications for public health in regions such as the Middle East where camel products are used. The global spread of MERS+ would be hastened by the flux of Middle Eastern refugee populations, potentially augmented by some malicious carriers on terrorist social networks. Large population flux has driven most of the great pandemics of world history. Lloyd’s report ‘Pandemic, potential insurance impacts’ (2008) highlights how with historic recurrence rates of 30-50 years it is prudent to assume that a pandemic will occur at some point in the future and how a repetition of the 1918 event could cause a global recession with estimated impacts ranging from 1% to 10% of global GDP. In the Lloyd’s City Risk Index 2015-2025 the combined average GDP over 10 years at risk from human pandemic for 301 cities is US$ 591.81 billion with Hong Kong, Moscow, Shanghai, Sao Paulo and Tokyo in the top five.

Source: Army Medicine (2014)

Bias induced by historical calibration



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5. Bias induced by historical calibration

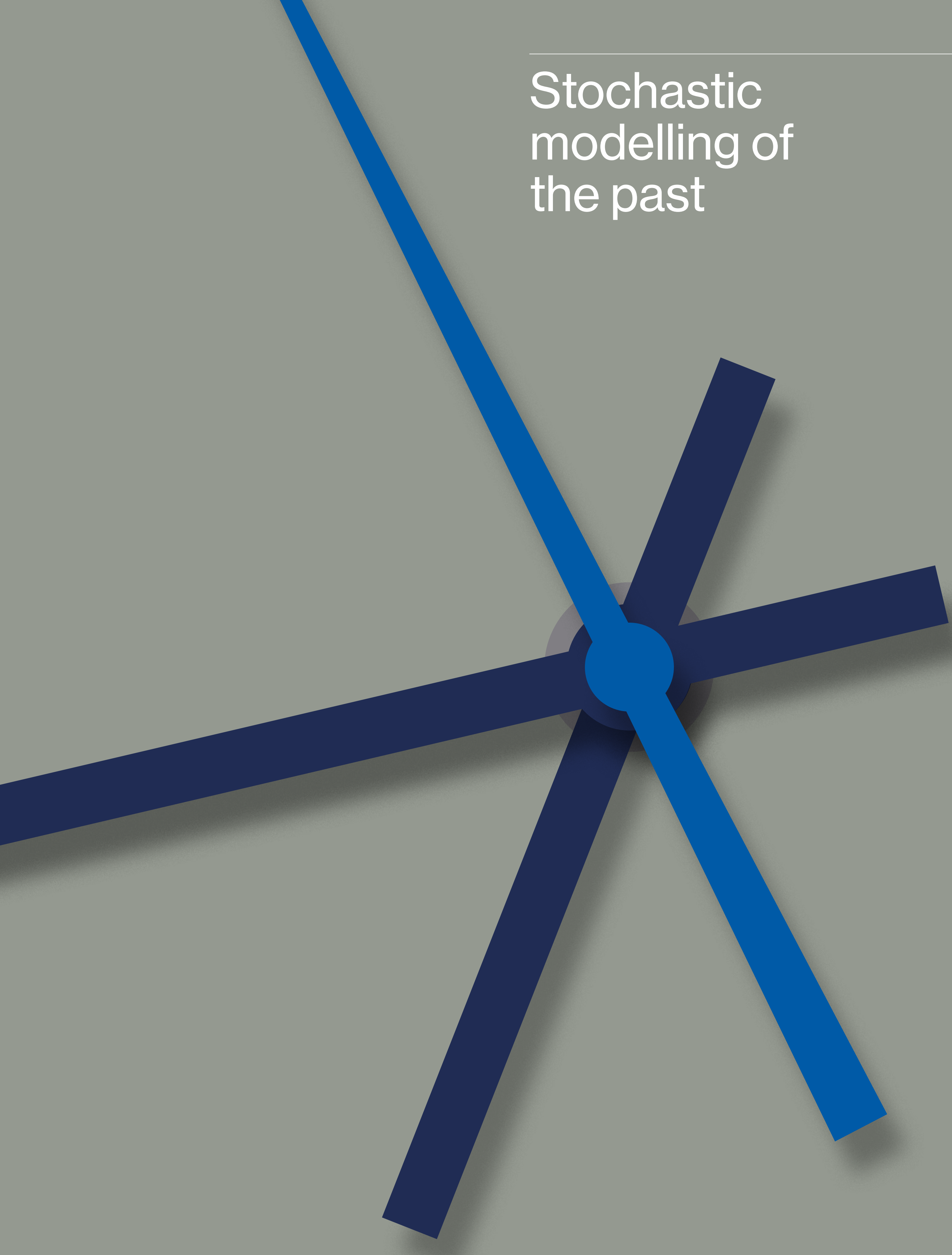
One of the concerns for insurance risk managers and regulators is over a common weakness in all the catastrophe risk models for a specific country and peril. Catastrophe risk modellers work independently of each other, and take different views on many topics where risk ambiguity exists. But bias can be generated if there are substantial common elements in the risk modelling for a particular peril. One way this can arise is if all models are calibrated too closely with sparse historical data, with numerous missing events at the top end of the range.

Perhaps the most notorious earthquake hazard example is the seismological blindness to the possibility of the Magnitude 9 earthquakes that occurred on 26 December 2004 and 11 March 2011. Retrospectively, Kagan and Jackson (2013) argued that the magnitude 9 earthquake off Tohoku in 2011 should not have surprised the seismological community. Since 1997, evidence had been steadily accruing for subduction zones to have indistinguishable upper magnitude parameters. The cumulative evidence of great earthquakes prior to 2011, including the 2004 Sumatra earthquake, could have provided warning of the possibility of a great M9 event offshore Tohoku.

As far back as 869 AD, the Jogan earthquake occurred, which was known to have caused a tsunami affecting much of the same coast as the 2011 Tohoku tsunami. Coastal geologists were however unable to establish the full evidence for the immense size of the 869 earthquake. For Sawai et al. (2012), it is thus an open question whether Earth science could have forewarned of the 2011 earthquake. But even if the 869 earthquake evidence was insufficient for earthquake warning purposes, insurers could have mitigated the bias by adopting their own view of the tsunami risk.

Long earthquake ruptures often result from propagation across different fault segments by jumping, bending and branching. The complex geometry of possible fault rupture tends to be greatly simplified in earthquake hazard models; often only past observed occurrences of convoluted ruptures are represented. The absence of other ruptures induces an element of systemic risk. In California, the deficiency of multi-fault ruptures was a latent systemic risk in earthquake hazard models until the Third Uniform California Earthquake Rupture Forecast UCERF3 (USGS, 2015). The earlier much smaller 2008 UCERF2 model predated the great M9 Tohoku earthquake, which alerted seismologists to this systemic risk.

Stochastic modelling of the past



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6. Stochastic modelling of the past

The historical past is just one of many possible realisations that might have happened. There is an anthropic bias in regarding the past as somehow special, rather like perceiving the Earth to be at the centre of the universe. This perception is reflected in statistical analysis of historical data where the past is traditionally taken as being rigidly fixed.

The inherent randomness induced by the passage of time can be recognised through stochastic modelling of the past. This exercise of re-running the tape of history can be undertaken for any peril for which historical records are kept. To date, this exercise has all too rarely been undertaken, partly because of the substantial effort required, and partly because of a lack of appreciation of the purpose and value of this undertaking. However, such effort would be rewarded by deeper risk insight for risk stakeholders, particularly for insurers.

6.1 Illustrating uncertainty: a simple hurricane resampling experiment

The HURDAT data set contains more than 150 years of hurricane tracks in the North Atlantic although arguably it is only the most recent 110 years of landfalling statistics that are really reliable. It has been a formidable effort to create this catalogue which continues to be revised and updated.

As noted, observed history is just one instance of what could have happened. The climate is a chaotic system and tiny fluctuations in global climate variables could have led to different outcomes. Therefore one should not assume that the observed past is an absolute measure of future outcomes. This is particularly the case for very rare events such as landfalling category 4 and 5 hurricanes. It is even true for something we might expect to be more stable, such as the observed annual average loss from past events.

It might be tempting to adjust the catastrophe model to "match" historical losses – but this could under or overstate the true risks if the combination of events and exposure concentrations was "unusual". More elaborate stochastic modelling experiments can be developed, but here is a simple catastrophe modelling experiment that can be carried out to demonstrate the uncertainty in historical data. Stress testing of catastrophe bond risk analysis may involve such a study.

Box 2: Catastrophe modelling experiment to demonstrate the uncertainty in historical data

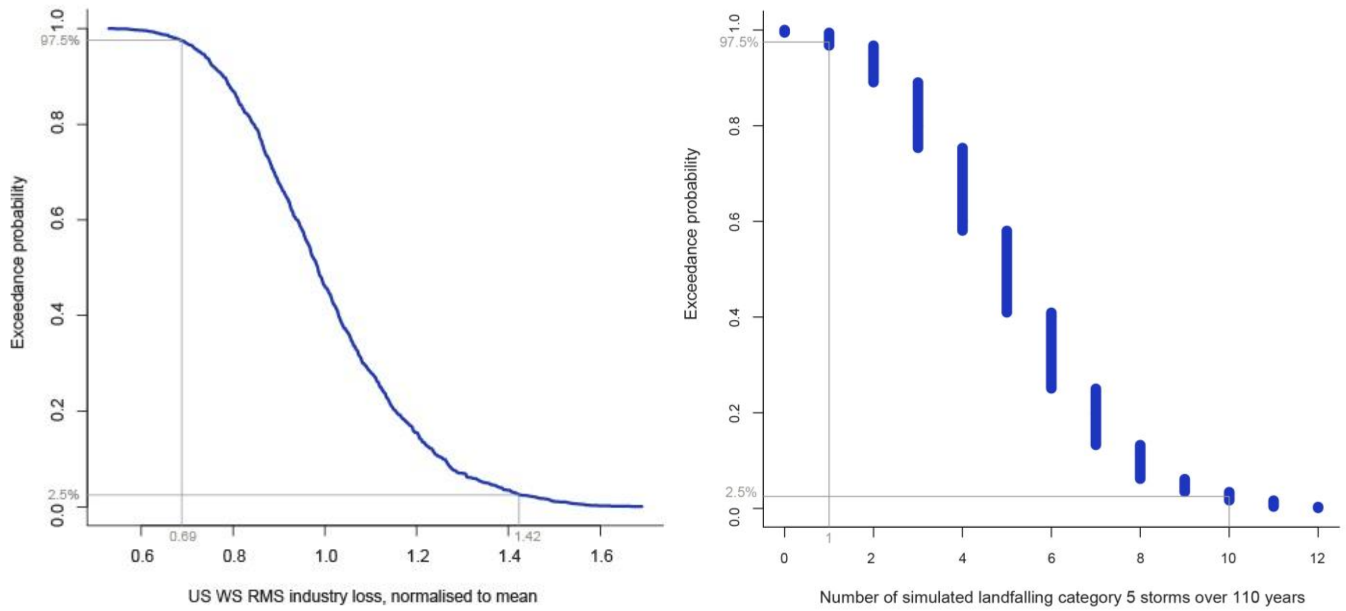
Step 1: simulate a counterfactual history

- Simulate hurricanes from given distribution into separate years (the usual Monte Carlo approach)
- Repeat 109 more times
- Calculate the average annual loss (or other statistic) over the 110 years – keep this number

Step 2: now repeat the above process for, say, 1,000 times

The method used for this experiment assumes perfect knowledge about the true underlying distribution that generates hurricane observation and aims to estimate the uncertainty arising just from slow convergence in a finite sample of observations. Using this method we see (in Figure 2, left) that the simulated annual average loss (blue) can be as much as 142% or as little as 69% of the true value normalised to 1.0 within a 95% confidence interval (grey). Using the same method we can count landfalling category 5 storms (say) and see (in Fig 2, right) that there is an average of 4.4 storms per 110 years, but anything between 1 and 10 would be in line with the model within 95% confidence. Given that any of these realisations could have occurred in the past 110 years we should consider how our view of hurricane risk would be different now, if we had observed 9 category 5s or just one. This illustrates the uncertainties in assessing extreme risks of this type and also illustrates why catastrophe models are painstakingly created. Lloyd's minimum standards require there to be formal processes to communicate material uncertainty to nominated committees and the board; counterfactual risk analysis could be a useful method to do this.

Figure 2: Catastrophe modelling experiment



6.2 Stochastic forensics

An aspect of catastrophe risk analysis which merits greater attention is the study of stochastic forensics. Whenever a crisis passes, there may be some legal, possibly criminal, enquiry into the underlying causes. However, it is rare for any scientific attempt to be made to assess the probability of different causal factors or the outcome likelihood. One high-profile stochastic forensic challenge, in which aviation insurers took a keen interest, was solving the mystery of the ill-fated Malaysian Airlines jet MH370 which disappeared on 7 March 2014, en route from Kuala Lumpur to Beijing. A probability distribution for the final resting place of the jet was derived using innovative Bayesian techniques (Holland, 2017). A prior distribution was defined by Malaysian radar, and a likelihood function was constructed using satellite data and analysis of the aircraft dynamics.

Since the past has a complex fractal structure, the further back in time that is investigated, and the more event branches that are followed back in time, the less clear it is what the contribution of a specific factor was to the overall outcome. Two examples, drawn from the diverse range of man-made and natural perils, are presented here. Both initiatives re-visit challenging crisis management decisions, over which there was some degree of legal controversy.

The first is an aviation accident. Near misses in civil aviation are quite common; on any given flight, there may be excursions from the flight plan that take the plane out of the scheduled safety zone. Some excursions may force a plane to return to its departure airport. Frequent flyers may well have experienced this trauma. Despite these excursions, crashes are extremely rare. As and when any problem arises, the flight crew are trained to keep the plane in the air until it can be landed safely. This is exemplified by the so-called ‘miracle on the Hudson’.

On 15 January 2009, US Airways Flight 1549 took off from LaGuardia airport in New York and was struck by a flock of Canada geese three minutes later. This aviation crisis might have evolved in many different ways. Captain Sullenberger skilfully glided the powerless plane to ditch in the Hudson River. All 155 people survived. Clearly, the outcome could have been far worse if the ditching had left the plane submerged, broken or ablaze. But could the upward counterfactual of a safe airport landing have been realistically achievable?

The National Transportation Safety Board used flight simulators to test the possibility that Flight 1549 could have returned safely to LaGuardia, 4.5 miles away or diverted to nearby Teterboro airport, New Jersey, 9.5 miles away. Only eight of the 15 runs to Teterboro succeeded but all four attempts to reach the nearest LaGuardia runway were successful. The NTSB report (2010) noted that an almost immediate turn was required; a simulation with a 35-second delay resulted in a crash. A turn would have endangered those on the ground, since returning to LaGuardia would have involved crossing Manhattan. Estimates of possible ground casualties might have been made with further simulations of the delayed decision scenario.

The recovery of black box recordings facilitates learning from aviation accidents by simulating how they happened. There is no comparable investigative process for natural hazards, but the question of scientific error in data interpretation did arise in the second example of stochastic modelling of the past. This relates to one of the most acrimonious debates in volcano crisis risk management: the mass evacuation in 1976 of the population at risk from a major eruption of La Soufrière volcano on the Caribbean island of Guadeloupe. International volcanological opinion was divided over the interpretation of the geological evidence: some thought this signified the imminence of a dangerous magmatic eruption; others were convinced that only a benign steam eruption would ensue. The latter ultimately were vindicated. But was the evacuation decision nevertheless justified? Reviewing all the evidence three decades later (Hincks et al., 2014), and synthesising it within the probabilistic framework of a Bayesian Belief Network (see Appendix A.2), the probability of an eruption was calculated, and exceeded the threshold that would have justified the evacuation on a cost-benefit basis.

6.3 Scenario event trees

Scenarios are essentially counterfactual histories of the future. Each scenario can be represented as a stochastic event tree generated from a specific initiating hazard event. This event tree has three main branches corresponding to:

[1] *Hazard footprint*. This maps the severity and spatial extent of the salient hazard measures for the initiating event. Especially critical are those areas within the hazard footprint where the hazard values exceed local engineering design parameters, or key impact thresholds for geotechnical phenomena such as landslides and liquefaction.

[2] *Primary loss footprint*. This corresponds to the direct action of the hazard on the exposure within the hazard footprint. Especially critical are vulnerable components of the critical infrastructure, controlling power, water, communications, transport, emergency response and other lifelines.

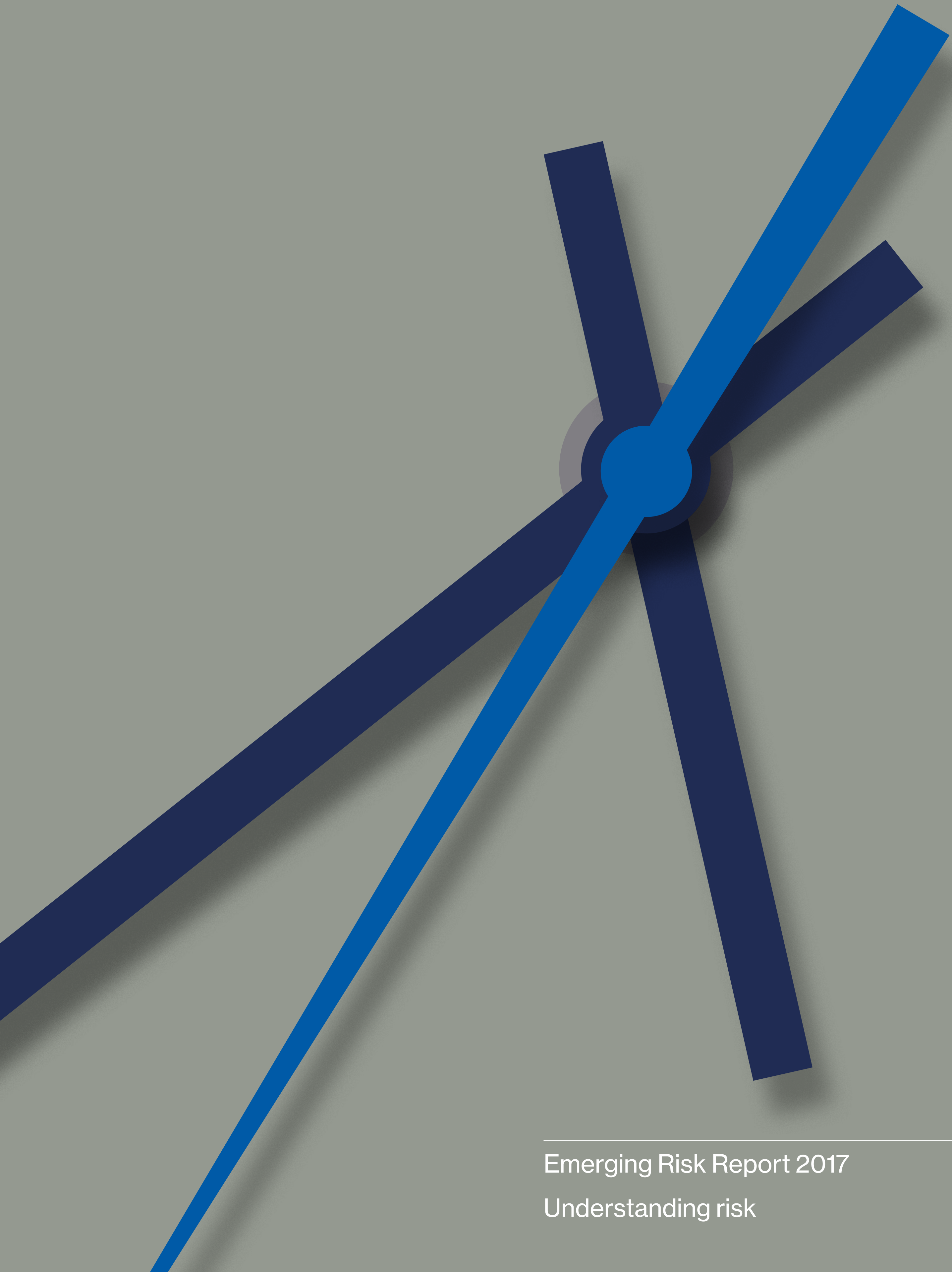
[3] *Secondary loss footprint*. This corresponds to the action of indirect secondary hazards on the exposure within the hazard footprint, supplemented by breakdown of critical infrastructure and other key industrial facilities causing economic bottlenecks.

The actual loss from a historical event can be regarded as the final node along a particular individual pathway through a stochastic event tree, starting with an initiating event, leading to specific hazard, direct loss and indirect loss footprints.

To illustrate the main event tree sequence of hazard, primary and secondary loss footprints, the M6.7 San Fernando, California, earthquake of 9 February 1971 is an instructive paradigm. The salient hazard measure for this initiating hazard event is the severity of seismic ground motion. High levels of ground shaking were recorded from this earthquake. At the Lower San Fernando Dam, high peak ground-acceleration levels as high as 0.5g were attained. The strong sustained shaking triggered a loss of strength of the embankment soils, which caused a massive slide in the upstream slope of the dam, and lowered the crest by about 10 metres. Fortunately, the dam did not fail. A detailed geotechnical analysis of the soil liquefaction was undertaken by Seed et al. (1989). This could be extended to assess the probability of dam failure for the downward counterfactual of more severe levels of ground shaking.

The primary loss footprint might have been more severe had the reservoir been at its maximum height, which it was in the previous year. Water could then have overtopped and eroded the dam. The dam might then have failed, causing the valley to be flooded with millions of tons of water. A UCLA study found that the casualty toll could have been between 71,600 and 123,400 people (Los Angeles Times, 2012) - a cataclysmic downward counterfactual. To put this huge number into perspective, the total number of California earthquake deaths over the past 60 years is about 200. California dam failure remains a catastrophe risk; damage to the spillway of the Oroville dam, following torrential rain in February 2017, led to the precautionary evacuation of 180,000 people.

Counterfactual disaster scenarios



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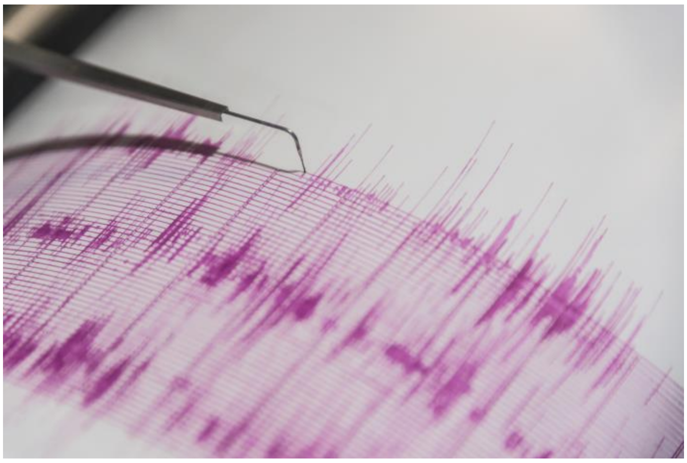
7. Counterfactual disaster scenarios

Lloyd’s maintains a set of mandatory Realistic Disaster Scenarios (RDS) to stress test individual syndicates and the market as a whole. RDS are derived from expert perspectives on the established – and therefore reasonably quantifiable – threat horizon. Especially where models are unavailable or of limited resolution, these RDS may be augmented by Counterfactual Disaster Scenarios (CDS) corresponding to actual historical near-miss circumstances that might have become major disasters.
Being rooted in history, CDS might be particularly insightful in the specification of alternative scenarios. Some possible CDS are outlined below.

7.1 New Zealand earthquake



The Kaikoura, South Island, New Zealand M7.8 earthquake of 14 November 2016 was an important earthquake, likened in stature to the great earthquake of 1855, and caused notable damage in Wellington, some of which was surprising to earthquake engineers. Counterfactually, it could have been worse. The rupture was intrinsically stochastic and had a complex pattern that could not have been predicted (Shi et al., 2017). Of the numerous faults known to have ruptured, only part of the Hope Fault ruptured, indicating that the earthquake magnitude might have been larger. Yet more fault ruptures might have been triggered. With the larger extended rupture geometry propagating towards Wellington, the duration of strong shaking would have been longer, and the damage there might have been considerable. A further downward counterfactual triggering scenario is that of an earthquake of M8+ on the interface between the Pacific and Australian Plates.

7.2 A major flood incident

The extratropical remains of a hurricane preceded a major North Sea storm on 9 November 2007. The UK Met Office forecasted strong winds combined with high tides. The actual recorded sea levels came to just 10 cm below the top of most of the sea walls in and around the Norfolk seaside town of Great Yarmouth (Met Office, 2007). Fortunately, the winds were largely offshore, resulting in the waves not being as high as they might have been. Also, the storm surge had lessened as it travelled down the coast and by early morning was 20-30 cm less than anticipated in previous days. This storm had similar meteorological characteristics to that associated with the great 1953 storm surge. Counterfactually, the storm surge levels might have been as high as actually forecast by the Met Office, and the East coast flooding might have been the worst since 1953.

7.3 Caribbean/US hurricane windstorm clash

Source: NASA Goddard Space Flight Center (2016)

Windstorm catastrophe models have progressively increased in resolution over the past several decades. But no matter how large the stochastic event set is for an Atlantic hurricane model, the event set cannot span the entire dense space of possible hurricane trajectories. Inevitably, some notable alternative variations of historical hurricanes may not be well represented in the stochastic event set, but vendors' model do optimise the event set so that characteristic tail events are included. Accordingly, counterfactual disaster scenarios can be simulated that are distinct in terms of hazard characteristics and loss potential from scenarios in catastrophe models. This makes CDS ideal for generating alternative scenarios, such as for Caribbean/US hurricane windstorm clash. A prime example is Hurricane Matthew in 2016, which skirted the coast of Florida after passing through the Caribbean, causing havoc in Haiti, the Dominican Republic, the Bahamas, Cuba, St. Vincent and the Grenadines. Counterfactually, emerging from the Caribbean, Matthew might have been one of the most destructive Florida hurricanes, making landfall at Palm Beach as a Category 4 hurricane. Counterfactually, US insurance losses might have been as high as US$30 billion, which is about 10 times what they actually have been (PCS, 2017). Most recently, hurricane Irma landed on the west coast of Florida and insurance claims are expected to be between US$35 and 55 billion (RMS, 2017). But hurricane Irma might have had a less westerly track and struck Miami at Category 4. The potential US insurance losses from this downward counterfactual were estimated at US$150 billion (Staletovich, 2017) by Karen Clark. She has developed Characteristic Events (CE), which are defined-probability events for specific peril regions. The CE footprints can be customised and moved around, providing a range of plausible losses.

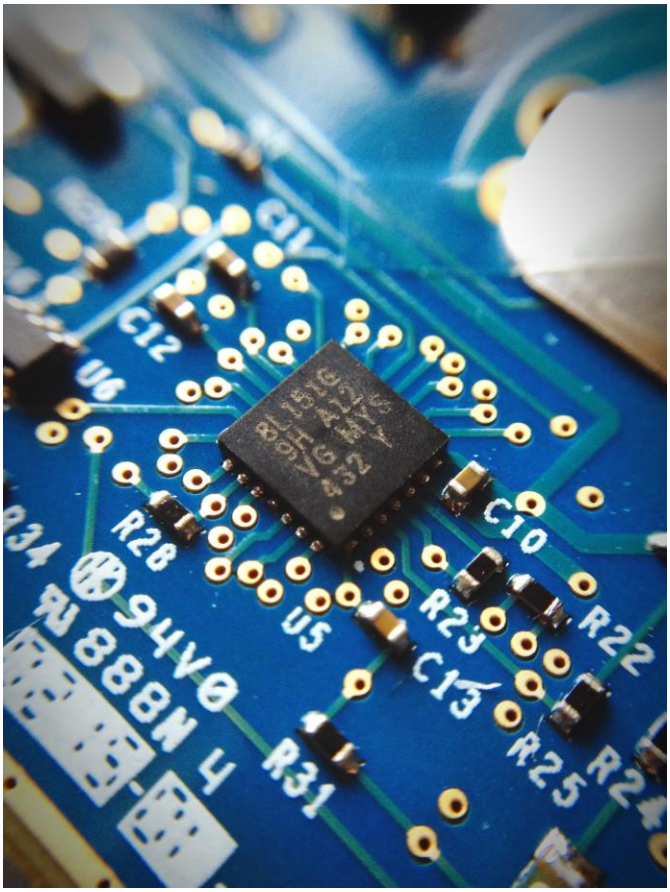
7.4 A 'Selby-type' liability loss

As described before (p.11), the Selby rail crash resulted from a chain of rather bizarre hazard circumstances, which vehicle insurers would not have anticipated. On the evening of 4 November 2011, another unusual English motorway accident occurred. Seven people were killed and 51 were injured in a multiple vehicle collision on the M5 motorway near Taunton. The date is significant. Smoke from a nearby Guy Fawkes fireworks display thickened the fog. Counterfactually, the smoke from the bonfire might have been much thicker still and drifted sufficiently to have rendered the fireworks display organiser liable for the consequent motorway losses should negligence be proved. Substantial liability claims might then have been shared between the insurers of the fireworks organiser, the host Taunton rugby club and by the respective vehicle insurers. These claims might have attained catastrophe levels if several coaches had been caught up in the pile up and the overall casualty toll reached several hundred.

7.5 Accumulation of casualties to members of sports team

Memories of the tragic loss of Manchester United players in the Munich air crash of 6 February 1958 were rekindled on 28 November 2016, when a charter flight LaMia 2933 from Bolivia to Colombia crashed due to lack of fuel, killing 71 of the 77 people on board (AIG, 2016). Most of the passengers were players or coaching staff of the Brazilian football team Chapecoense. This is a disaster that might well have happened before. On 8 of the 23 flights since 23 August, fuel and loading regulations had been contravened; one of these transported another football club. The same British Aerospace plane had carried Argentina's national team from a match in Brazil to Colombia earlier in November. It had also transported Venezuela's national team in the past. For whatever reason, accidental or malicious, a charter plane carrying a team of extremely highly valued footballers can crash. The most valuable sports teams in Europe and the US are worth billions of dollars (Forbes, 2016).

7.6 Terrorism accumulations other than Manhattan



In 2006, for the fifth anniversary of 9/11, Al Qaeda devised a terrorist plot that it threatened would be bigger than 9/11. Had the plot not been interdicted, as many as seven transatlantic flights from Heathrow might have been blown up by liquid explosive bombs. The destination cities were New York, Washington DC, Chicago (2), San Francisco, Toronto and Montreal. Counterfactually, each bomb might have been detonated on the approach to landing, so that the falling debris would have been scattered like shrapnel over a wide urban area, causing injury and damage. Numerous insurance lines of business might have suffered major losses. The disruption to the civil aviation industry would have been immense, given the lack of public confidence in flight safety afterwards.

7.7 Global cyber risk

A cyber ransomware attack began on 12 May 2017 and spread globally, taking advantage of an exploit developed by the US National Security Agency. Fortunately, a patch for this exploit had been issued by Microsoft on 14 March 2017, and only a small proportion of computers were vulnerable. Counterfactually, the attack might have been launched before the patch, in which case the global loss would have been very much greater. The virus would also have spread further had a kill switch associated with an unregistered domain name not been accidentally found.

Regulatory insights

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8. Regulatory insights

Stochastic modelling of the past is complementary to stochastic modelling of the future, and counterfactual risk analysis is a logical supplement to prospective catastrophe risk analysis. As such, this type of historical analysis provides a valuable independent additional tool for regulatory stress testing, checking and making sense of the results of catastrophe risk models.

In the insurance management of extreme risks, Solvency II requires an assessment of tail risks for all material region perils for the estimation of the solvency capital requirements. The risk analysis challenge imposed is reflected in the following comment (EIOPA, 2014):

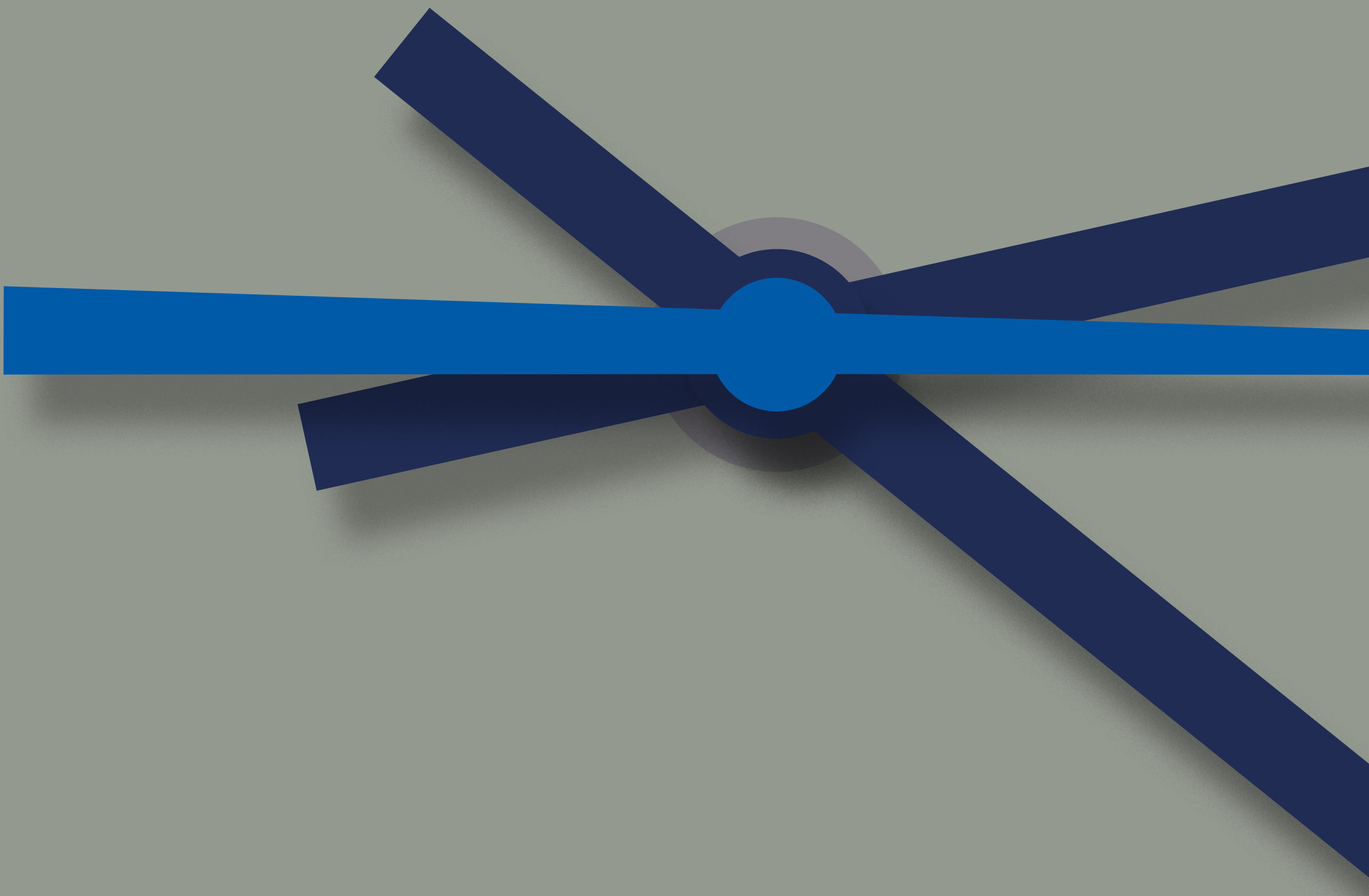
"Probabilistic catastrophe risk models are not available for all the perils and countries in scope. In addition, several decades of scarce loss experience are not sufficient to calibrate a one in two hundred year loss level for any natural peril. Hence, in an attempt to ensure consistency and risk adequacy much of the calibration assumptions were based on expert judgment and scenario-based approaches were chosen."

Counterfactual risk analysis helps to address the kind of modelling shortcomings expressed above. Where there are no catastrophe models for a specific peril-country combination, simplified models can be constructed from counterfactual analysis of the available historical record (Woo, 2016).

Where catastrophe models do exist counterfactual risk analysis can be used to benchmark modelled loss estimates against scenarios that are plausible and easy to understand. In particular, this supplementary analysis would be instructive in guiding and informing expert judgment, and in prescribing extreme scenarios.

Furthermore, counterfactual risk analysis offers additional support in communicating risks, and counterfactual thinking should be understood by insurers. Catastrophe models may be open to criticism for a lack of transparency. Inevitably, this 'black-box' critique makes risk communication more difficult, especially to senior management who may be held to account for their understanding of the models and how they are used, not just be informed of the model output. Under Solvency II, Pillar 2, the Board needs to be informed of the reliability and adequacy of technical provisions by a person with an actuarial function. The fact that downward counterfactuals are anchored to actual historical experience, rather than being hypothetical future scenarios, facilitates coherent explanation, deeper understanding and more effective communication. In addition, a downward counterfactual exemplifies the PRA concept of an ENID: Event Not In Data (Prudential Regulatory Authority, 2014). It may not be clear or convincing to the Board how realistic a future abstract scenario actually is. By contrast, a downward counterfactual may be explained succinctly as a historical scenario that might have happened if things had turned for the worse.

Practical applications in modeling activities for P&C (re)insurance



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9. Practical applications in modelling activities for P&C (re)insurance

So far this report has outlined the use of downward counterfactual risk analysis:

- in improving risk awareness and communication through better understanding of tail risk scenarios,
- for gaining confidence in the tail of your catastrophe risk distribution, and
- in the quantification of catastrophe risk

Notably, the link between counterfactual analysis and decision-making has been demonstrated with the recent US hurricane activity. There has been considerable discussion among (re)insurance professionals about events such as Irma in 2017 and Matthew in 2016, whose initial forecast tracks if realised, could have been significantly more damaging (refer section 7.3). These downward counterfactual analyses have heightened risk perceptions and may well influence risk transfer decisions.

In this section however, we explore how, for catastrophe risk quantification, counterfactual risk analysis can be applied in all three core catastrophe modelling activities of a P&C (re)insurer, namely pricing, capacity management and capital calibration.

As mentioned in the executive summary counterfactual risk analysis and the framework presented in the report can be applied to two distinct categories of risk quantification: traditional probabilistic natural catastrophe modelling and data-poor scenario-based modelling (especially for emerging risks).

9.1 Pricing non-modelled catastrophe risk

In the case of pricing using an experienced-based frequency-severity distribution, counterfactual risk analysis can help calibrate the tail of loss distributions, with limited distortion to the expected loss. For example:

- As highlighted in Section 7 Lloyd's RDS could be augmented by counterfactual risk analysis and could be applied to calibrate a frequency – severity distribution.

- There are a number of region-perils where historical losses are limited and no major vendor models exist. In these cases, it is not uncommon to see a catastrophe excess of loss treaty pricing calibrated based on a single data point. For example, in the case of Saudi flood, Thai floods or Canadian wildfires the steps in Box 3 can be applied. A practical application and exploration of the 2016 Fort McMurray wildfire alternative realities has been carried out in a recent study (Seria, 2016).

9.2 Pricing modelled catastrophe risk

For vendor modelled region-perils, there are typically some non-modelled elements. Here we consider how counterfactual risk analysis can assist in modelling two secondary perils.

For example, for wettest US hurricanes (e.g. Harvey) the flood losses are not (currently) explicitly modelled by the two main model vendors. Tropical storm Alison (2001) is another recent example of a US hurricane that generated significant precipitation-induced flooding. We also have additional examples further back in the historical record (e.g., 1950 hurricane Hiki and 1938 Long Island Express hurricane) where non-surge precipitation-induced flood components were material. We may also have near-misses where flooding could have been significant had environmental conditions been different.

Similarly, tsunami is a secondary peril not always explicitly modelled in earthquake models.

The illustrative steps in Box 3 demonstrate how counterfactual risk analysis can help quantify cat risk due to secondary perils. As these secondary perils get incorporated into updated vendor models, the approach in Box 4 can help validate the updated model.

Box 3: Pricing non-modelled catastrophe risk

1. Identify the key environmental factors (e.g., astronomical high tide, heavy rainfall, etc.) underlying the set of conditions that led to these limited observed events (or near-misses)

2. Collate hazard data (e.g., wind speeds, rainfall, inundation, etc.) or other indicators (e.g. sea surface temperature).

3. Build a catalogue of environmental conditions or hazard states based on observed data and indicators. One hazard state here represents a combination of environmental factors and indicators. You may wish to expand the catalogue based on plausible scientific scenarios as yet unobserved. Simulation could be applied here to create much larger samples by taking random picks from a hazard distribution to yield realisations for each environmental factor.

4. This yields a catalogue of periods, where a few rare cases represent extreme hazard states (i.e., the worst picks for each of the environmental factors) expected to cause significant destruction. We also expect to see some less extreme but still damaging hazard states but the vast majority would comprise hazard states that generate no, minimal or moderate damage.

5. Simulate losses: for each period in the catalogue, simulate losses as outlined in the mathematical appendix. This yields a set of damage ratios to which exposure data may be applied.

6. Apply terms and conditions to yield a period loss table (PLT).

7. Compute the expected loss / risk premium as the average loss across all periods assuming all periods are equi-probable.

8. Sense check the modelled likelihood of observed losses against expectation.

Box 4: Pricing modelled catastrophe risk

1. Identify stochastic events in the earthquake catalogue that are deemed tsunamigenic or for hurricane, are prone to precipitation-induced flooding (e.g. that stall post-landfall).

2. Build characteristic footprints to determine extent of inundation for groups of event IDs.

3. Estimate damage given inundation due to the secondary peril.

4. Compute loading factors for each event ID group where the loading factor represents the additional loss due to the secondary peril and apply to relevant event IDs.

5. Simulate losses to the (re)insurance contract based on the updated event loss table / year-loss table.

6. Sense-check against observed loss data.

9.3 Capacity management

For many monitored region-perils, capacity is based on a single risk-metric (e.g., 1:100 occurrence exceedance probability for wind and flood, 1:250 for earthquake). For non-modelled region-perils, sum of exposed limit is invariably the operational metric used for capacity monitoring. Counterfactual risk analysis can help derive a probable maximum loss (PML) that can be used to set risk tolerances and track against them. One option is to follow the steps in Box 3 for pricing non-modelled region-perils to yield an exceedance probability curve from which the relevant risk metrics can be selected and value extracted. Alternatively, deterministic (tail risk) counterfactual scenario analysis can be developed. Operationally, to enable monitoring, the scenario would need to be designed such that it is sensitive to changes in the in-force (re)insurance portfolio. For example, a flood or wildfire footprint which can be applied to geo-coded exposures with deterministic damage ratios to generate a loss estimate. In such a case, the PML moves in line with exposures.

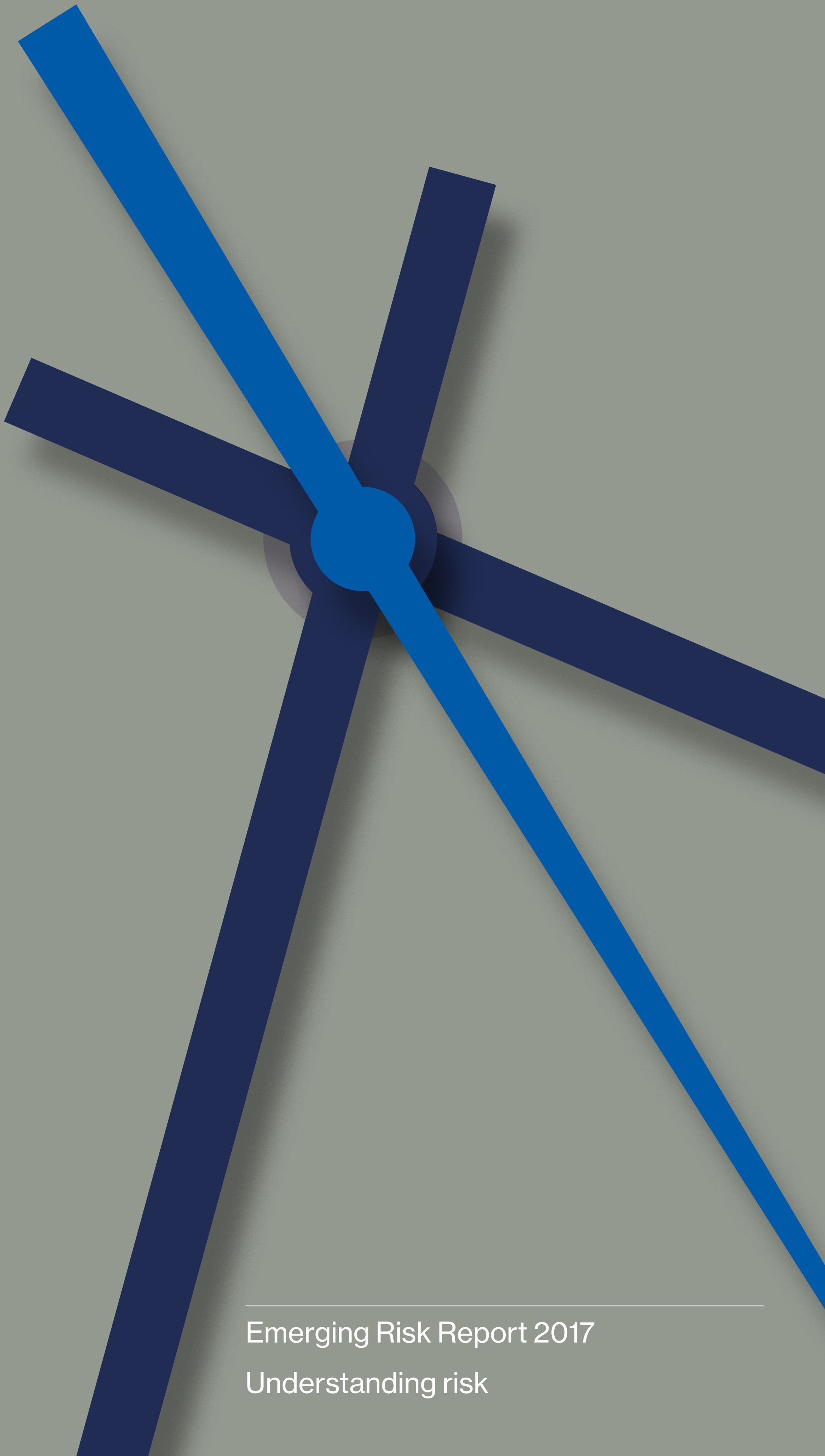
9.4 Capital calibration

For Solvency Capital Requirement calibration, the above quantification steps may also be applied in calibrating the cat risk component of an internal model. This has a number of benefits:

- These methods allow aggregation of year loss tables (YLTs) in a consistent manner across all region-perils.
- In this way, diversification benefits may be clarified as the worst 1% of losses in the all-perils YLT will include counterfactual tail events from non-modelled region-perils.
- Consistency across pricing, capacity management and capital calibration (where the same counterfactual risk analysis approaches are adopted)
- Reinsurance modelling and hence design (particularly of aggregate deals) are improved through the use of stochastic (physically-based) counterfactual models that provide insight into erosion from high-frequency perils.

These approaches can be developed cheaply and efficiently and provides a useful starting point for the development of more sophisticated models in open source loss modelling platforms such as OASIS.

Conclusions



10. Conclusions

Counterfactual risk analysis can be applied to any set of risks, but is particularly useful for those that have limited loss history. It could help create structured, transparent, scientific and evidence-led scenarios for non-modelled risks (especially emerging risks) for which there is not much data, and could be used to validate traditional probabilistic natural catastrophe modelling.

Counterfactual risk analysis helps address the bias that can be inherent in some models that are based on the same data sets. By expanding the data available based on what could have happened, these models can be built with less reliance on single-source data, which might improve their accuracy

The downward counterfactual disaster scenarios included in this report could be used to augment Lloyd's existing realistic disaster scenarios. Downward counterfactual risk analysis provides an additional useful tool for regulators to stress-test, check and back-test catastrophe risk models.

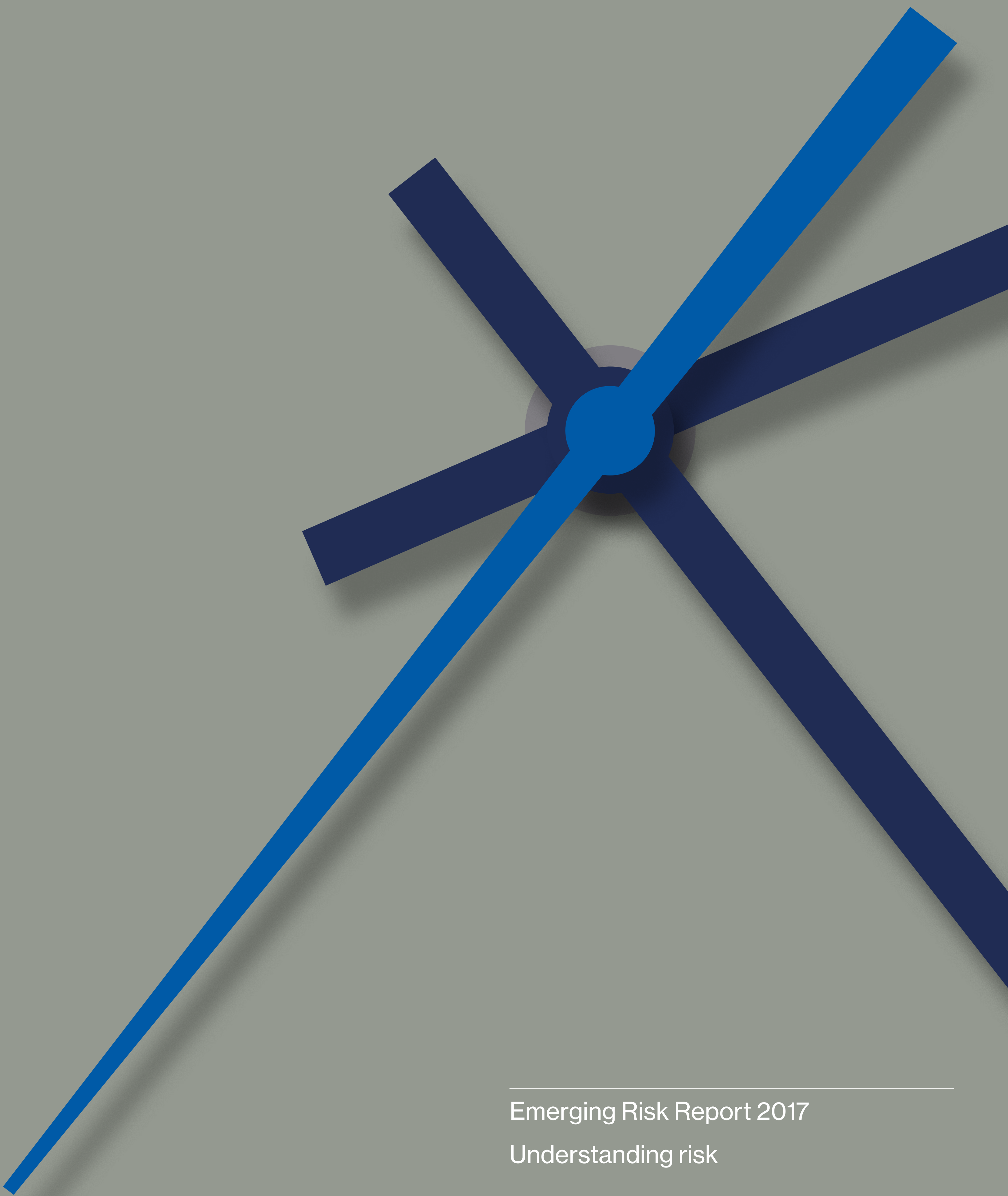
It could also help them communicate future risks and model uncertainty to board members, policyholders, policymakers and risk managers, as well as non-experts, as downward counterfactual examples are always based on actual historical experience.

For catastrophe risk quantification, counterfactual risk analysis can be applied in all three core catastrophe modelling activities of a P&C (re)insurer, namely pricing, capacity management and capital calibration.

Despite the benefits listed above, counterfactual analysis is rarely undertaken because of the substantial effort required, and because its purpose and value are underestimated.

We believe this is a useful addition to the suite of tools insurers and risk managers already use to analyse risk. This report helps insurers do this by describing how counterfactual analysis can be carried out in practice and it is a starting point for further applied research into counterfactual analysis of historical events and their characteristics.

Mathematical Appendix



Emerging Risk Report 2017

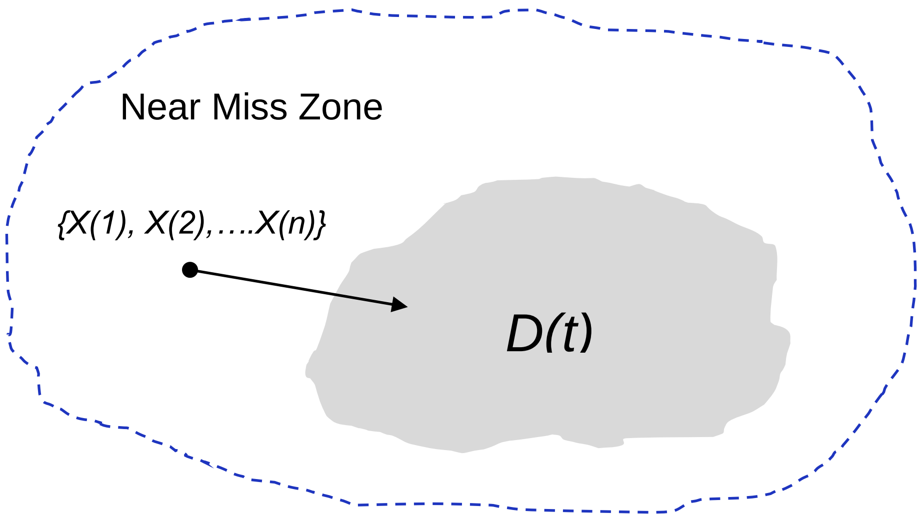
Understanding risk

A. Mathematical appendix

The hazard state of a system can be described as a complex time-dependent function of a number *n* of underlying hazard variables, some of which may be hidden and not directly observable: $X(1), X(2), \dots X(n)$. At various times *t*, a particular domain $D(t)$ of the space of underlying hazard variables becomes dangerous to an insurance risk portfolio, and some external agent of physical force strikes the portfolio. It is the catastrophe modeller's task to understand, measure and chart the extent of the dangerous domain of hazard variables $D(t)$.

In particular, there are combinations of the input variables $X(1), X(2), \dots X(n)$ which lie just outside this dangerous domain, within the near miss zone shown as dotted below, which may be dynamically perturbed to fall within the dangerous domain (see Figure 3). Furthermore, there are zones within the interior of the dangerous domain itself that can be perturbed into very much more dangerous regions of high loss amplification. Fresh insights into the dangerous domain of hazard variables $D(t)$ can be gained from searching explicitly for downward counterfactuals. Such a search is not prioritised by catastrophe risk modellers.

Figure 3: Perturbation of the system state X into the dangerous hazard domain D



Unforeseen or neglected disaster scenarios, including Black Swans, may be discovered through diligent exploration of obscure downward counterfactuals. In the absence of a deliberate search, significant risk factors may easily be missed, especially human risk factors. For example, one exogenous variable that can influence flood risk significantly, but may be overlooked, is the human factor of water management policy. Quite apart from adverse meteorological and hydrological conditions, a river system state may be perturbed to fall within the dangerous domain of flood risk if imprudent water management decisions are made.

The catastrophic Thai floods of 2011 provide an important and costly illustration. Business interruption insurance losses are sensitive to supply bottlenecking and accordingly can be surprisingly high, as they were for the Thai floods.

As highlighted by the Lloyd's and Arup report (2017) 'Future cities: building infrastructure resilience' the direct impact of Bangkok's flooding included many hundreds of deaths, and around US$45.7 billion in direct economic damages nation-wide (Aon Benfield, 2012) – only ~ US $12 billion of which were insured losses (Acclimatise UK, 2016). Further afield, interruption to industry and manufacturing in Bangkok set back global industrial production by 2.5% (United Nations Office for Disaster Risk Reduction, 2012).

With some downward counterfactual thinking, a flooding lesson might have been learned in 1995, so that it did not happen in 2011. Very similar rainfall conditions were observed historically in 1995 as in 2011 in the Chao Phraya river basin. But many of the facilities that were flooded in 2011 did not flood in 1995, though the rainfall conditions were comparable. Crucially, during the 1995 flood, much of the runoff was stored in two dams. In 2011, fearing that dam water levels might remain very low as they were the previous year, irrigation water managers kept water levels high before and during the rainy season. This resulted in the dams being full in late September 2011, and vast amounts of water had to be released.

A.1 Stochastic simulation of historical events

As is clear from the events of the MH370 Malaysian passenger jet, which went missing in 2014, the past is not as familiar as might be supposed. Interchanging time and space, the past can be explored, rather like a foreign country. Just as a tourist can spend a vacation in one foreign city, so a risk analyst can spend a year focusing on one historical event. Indeed, an entire book (Davey et al., 2016) has charted the sophisticated use of Bayesian methods for weaving together the multiple thin strands of evidence that eventually yielded an overall probabilistic assessment of the final resting place of the Malaysian Airlines jet.

Insurers would know that evidence can be used to update the prior probability that a future event has a particular characteristic. Less familiar is that evidence can be used to update the prior probability that a *past* event had a particular characteristic. Thus it is possible to state that there is an x% chance that the MH370 ended up in a specific spatial zone of the Indian Ocean in March 2014, and that there is a y% chance that the 869 Jogan earthquake in Japan generated a tsunami covering a similar area to that of the Tohoku earthquake of 11 March 2011. But whereas with future events it should be possible to confirm a characteristic, with historical events this may well be impossible. Fragments of MH370 have washed up ashore, but the bulk of the plane may never be located.

The power of Bayesian methods for the stochastic simulation of historical disasters is demonstrated by this highly complex and technically demanding case study. More generally, a fundamental approach for the implementation of counterfactual disaster risk analysis involves the application of innovative Bayesian methods to make post-dictions of the past, in contrast with predictions of the future. In particular, Bayesian Belief Networks can be used as an effective tool, as referenced in the next section.

A.2 Catastrophe modelling based on precursory states

Consider a peril for which actual major loss event data in a particular region are very sparse. Construction of a catastrophe risk model for such a peril-region combination is especially challenging. However the task is easier if precursory incident, or near miss, data are quite common. For man-made hazards, examples of precursory incidents are terrorist plots, cyber hacking, wildfire arson, transport and industrial accident near misses, and political unrest. For natural hazards, examples of precursory incidents are periods of volcanic unrest, earthquake tremors, sustained heavy rainfall, atmospheric depressions, and emerging epidemics.

The more ample historical dataset of precursory incidents can be used to construct a catastrophe model in the following manner. The various types and combinations of precursory incidents define a set of distinct precursory states. Expressed in mathematical terms, denote the various precursory states for a given peril as $\{I_j | j = 1,2, \ldots N\}$ and let the multivariate probability distribution of the precursor variables be $f(I_1, \ldots I_N)$ then the probability of the loss exceeding a given threshold (the Exceedance Probability or EP) is calculated as:

$$P(L > L_T) = \iint P(L > L_T | I_{1,} \dots I_N) f(I_{1,} \dots I_N)$$

In practice the link between the precursor variables and losses may be poorly understood – but the links between hazard variables $(H_1, .. H_M)$ say, and losses are well studied. For example engineering studies combined with prior loss statistics can give us "Vulnerability Functions" which are well known from catastrophe models.

Denote the multivariate Vulnerability function by $P(L > L_T | H_1, .. H_M)$.

Now suppose that the multivariate distribution between the precursor variables and the relevant hazard variables can be expressed as $P(H_1, .. H_M | I_{1,} \dots I_N)$. This is where counterfactual analysis comes in – we look at past values of the indicator variables and determine what values the hazard variables might have taken. We can start with the values the indicator variables took in actual past events and perturb them in scientifically valid ways – and we can also start with other examples where the indicators did not lead to a loss producing hazard event but might have done. We might wish to start with a subset of these indicators such as "near miss" tables (which may be available if industry collects them as they do in aviation for example). Given this hazard-indicator relationship we can now restate the Exceedance probability calculation as:

$$P(L > L_T) = \iiint P(L > L_T | H_1, \dots H_M) P(H_1, \dots H_M | I_1, \dots I_M) f(I_1, \dots I_M)$$

It may help to illustrate this using a typical hurricane example. In this case the indicator variables might be key features such as I_1=*ENSO index* , I_2=*Sea surface temperature* , I_3 = *location of tropical cyclone generation* and so on. The key hazard variables might be H_1=*Windspeed at landfall*, H_2=*forward speed of cyclone*, H_3=*Radius of maximum wind.* The reason that multivariate distributions are needed is also illustrated by this example because we know that I_3 is affected by both I_1 and I_2. This approach allows us to capture correlations or dependencies between the indicators which will flow through to the hazard variables.

In the case where the precursory states are independent we can look at the marginal distributions of the precursory state $f(I_j)$. This may be estimated approximately from experience data acquired during the time period of peril observation. Then the annual frequency of loss L exceeding a high threshold L_T is written as the following summation over the range of potential precursory states:

$$Freq(L > L_T) = \sum_j f(I_j) * \Pr(L > L_T | I_j)$$

The second term in the summand is the probability that the loss *L* exceeds L_T , conditional on the occurrence of a single precursory state I_j. As in the general case above, precursory states might evolve into hazard states. Specifically, the second term in the summand can be expressed as a sum over a complete set of hazard states H_k exceeding a critical intensity threshold.

$$\Pr(L > L_T | I_j) = \sum_k \Pr(L > L_T | H_k) * \Pr(H_k | I_j)$$

Here the stochastic transition of precursory states into hazard states is expressed in a probabilistic manner. The hazard state then transitions into a loss state.

Figure 4: Transition from precursory state to hazard state to loss state

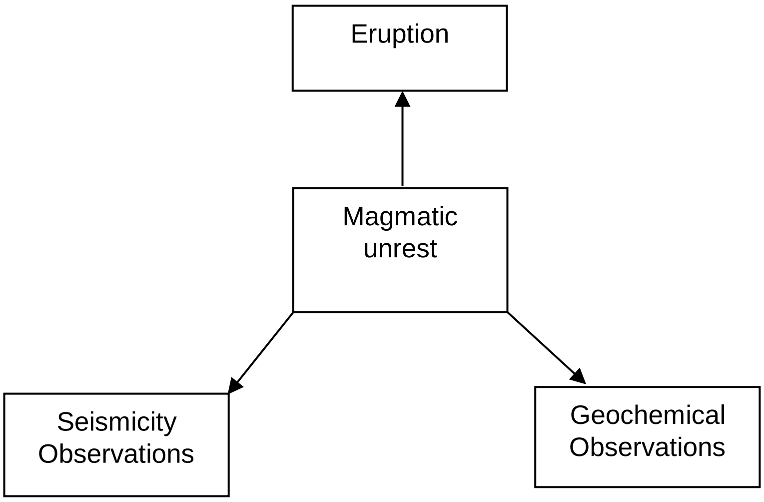
Precursory State → Hazard State → Loss State

Parameterisation requires as large a database of precursory states, as can be compiled. An underlying stochastic dynamic model of the precursory/hazard process is also needed. This might involve construction of a Bayesian Belief Network, which is a graphical model for representing knowledge, which preserves causality (Pearl, 2009). Illustrative examples are given here for a man-made peril (terrorism) and a natural peril (volcanic eruption).

In the context of terrorism, I_j would correspond to preparatory states of attack plotting with different weapon modes and multiplicities, e.g. light military arms, vehicle bombs of various sizes, weapons of mass destruction etc.. The hazard states H_k would correspond to the complete event set of successful attacks against notable targets. $\Pr(H_k | I_j)$ is calculated from the security interdiction and technical failure rates of notable plots, combined with targeting likelihoods – this is the counterfactual process. As for the general case $\Pr(L > L_T | H_k)$ depends on the vulnerability of the portfolio at risk to the hazard states H_k , and is calculated using engineering loss analysis familiar from catastrophe risk modelling. In countries with very proficient counter-terrorism forces, successful terrorist attacks are few, but the number of plots may be considerable. Counterfactually, any of these plots might have slipped through the counter-terrorism net.

In the case of the volcanic eruption peril, I_j would correspond to states of volcanic unrest, evidence of which is accumulated from a combination of seismic, geodetic, geochemical and geomagnetic monitoring. Counterfactually, a state of unrest might lead to an eruption. The hazard states H_k would correspond to different sizes and modes of eruption state. $\Pr(H_k \mid I_j)$ can be calculated from detailed construction of a Bayesian Belief Network (BBN) of volcano dynamics – this is the counterfactual step. An elementary BBN is displayed in Figure 5 (Hincks et al., 2014). The arrows indicate the direction of causality or influence. The conditional loss distribution $\Pr(L > L_T \mid H_k)$ can be calculated using hydrodynamic models of pyroclastic, lava and lahar flow to estimate the extent and severity of damage.

Figure 5: BBN for magmatic unrest leading to an eruption



References

AIG. 2017. Investigation COL-16-37-GIA Fuel Exhaustion Accident on 29, November 2015 Aircraft AVRO 146-RJ85, Reg. CP2933. [online]. Available at: http://reports.aviation-safety.net/2016/20161128-0_RJ85_CP-2933.pdf

Army Medicine, 2014. Ebola response training. [online]. Available at: https://www.flickr.com/photos/armymedicine/15650702011/in/photolist-pQZWrR-pRiLTN-p4DyNd-p4Esuu-pJ3TCY-p4Muoe-p4JCbf-p4JB8J-oUrjyt-q1mpj4-pJ8MKL-pJ4VcM-pBoeo6-q1yUL7-p4EcZN-q1mQyT-pYqBzq-p4JA7W-p4JD6w-p4H1WZ-pJ4drQ-pJ2q4x-pXEJyd-pS9csF-pJ5koc-quXEJF-q182Vr-pYmc9E-pAdmdm-qBvTMp-oq68Cn-qK6qsU-peHyeC-oL2XCq-qMiYX3-pQoc6L-qXGSbN-mxvLjF-pHmjS4-pqsg5M-pyN4Vz-pQo9Qo-oL34iy-prqyqh-qMj1Th-pGTBPV-peH3wm-ossh3B-pquaWE-pqrzsG

Annan, N. 2014. Violent conflicts and civil strife in West Africa: causes, challenges and prospects. Stability, Vol. 3. [online]. Available at: http://www.stabilityjournal.org/articles/10.5334/sta.da/

BBC. 2016. Hatton Garden jewellery heist: Final three guilty over £14m burglary. [online]. Available at: http://www.bbc.co.uk/news/uk-england-35315472

CAIB. 2003. Columbia Accident Investigation Board Report, Volume 1 NASA. [online]. Available at: https://www.nasa.gov/columbia/home/CAIB_Vol1.html

Chan, M. 2016. Italian Pilot Threatened to Crash Plane If Wife Left Him. Time, 7 March. [online]. Available at: http://time.com/4249365/italian-pilot-crash-plane-wife/

Conti, M. 2015. Another Close Call as Blizzard Juno's Storm Surge Peaks at Low Tide. [online]. Available at: https://northendwaterfront.com/2015/01/another-close-call-as-blizzard-junos-storm-surge-peaks-at-low-tide/

Das, K.N. and Spicer, J. 2016. How the New York Fed fumbled over the Bangladesh Bank cyber-heist. Reuters, 21 July. [online]. Available at: http://www.reuters.com/investigates/special-report/cyber-heist-federal/

Davey S., Gordon N., Holland I., Rutten M., Williams J. 2016. Bayesian methods in the search for MH370, SpringerOpen. [online]. Available at: http://www.springer.com/gb/book/9789811003783

Davies, R. 2017. Drone flew within wingspan of plane approaching Heathrow. Guardian, 31 March. [online]. Available at: https://www.theguardian.com/technology/2017/mar/31/drone-wingspan-plane-approaching-heathrow-near-misses

DeBono, E. 1977. Lateral thinking. Penguin Press, London.

DHS. 2006. US Department of Homeland Security Report. [online]. Available at: https://www.dhs.gov/sites/default/files/publications/cfo_par2006_fullreport.pdf

EIOPA. 2014. The underlying assumptions in the standard formula for the Solvency Capital Requirement. EIOPA-14-322. [online]. Available at: https://eiopa.europa.eu/Publications/Standards/EIOPA-14-322_Underlying_Assumptions.pdf

Forbes. 2016. The World's Most Valuable Soccer Teams 2016. [online]. Available at: https://www.forbes.com/sites/mikeozanian/2016/05/11/the-worlds-most-valuable-soccer-teams-2016/#193957f073b0

Hincks, T.K., Komorowski J-C, Sparks S.R.J., Aspinall W.P. 2014. Retrospective analysis of uncertain eruption precursors at La Soufrère volcano, Guadeloupe, 1975–77: volcanic hazard assessment using a Bayesian Belief Network approach. J. Applied Volcanology, Vol.3.

Hoffman B., Reinares F. (2014) The evolution of the global terrorist threat. Columbia University Press, New York.

Holland, I.D. 2017. The use of burst frequency offsets in the search for MH370. ArXiv:1702.02432v1. DSGT, Australia.

Howell, E. 2013. Columbia Disaster: What Happened, What NASA Learned. Space.com, 1 February. [online]. Available at: https://www.space.com/19436-columbia-disaster.html

IAEA, 2007. IAEA Issues Report on Kashiwazaki-Kariwa Nuclear Plant. [online]. Available at: https://www.iaea.org/newscenter/news/iaea-issues-report-kashiwazaki-kariwa-nuclear-plant

Jenkins P. 2003. Images of terror. Aldine transaction, New Jersey.

Jenkins, B.M. 2006. Unconquerable nation. RAND report, Santa Monica.

Joscelyn, T. 2016. AQAP publishes insider's account of 9/11 plot. [online]. Available at: https://www.longwarjournal.org/archives/2016/02/aqap-publishes-insid-story-of-911-attacks.php

Kagan, Y.Y. and Jackson, D.D. 2013. Tohoku earthquake: a surprise? Bulletin of the Seismological Society of America, Vol. 103, pp. 1181-1194.

Kahneman, D. 2011. Thinking, fast and slow. Allen Lane, London.

Laska, S. 2004. What if Hurricane Ivan had not missed New Orleans? Natural Hazards Observer, Vol.XXIX, No.2. [online]. Available at: http://onlinelibrary.wiley.com/doi/10.1111/j.1475-682X.2008.00232.x/pdf

Leiber, F. 2010. Catch that zeppelin! In: Alternative histories (I. Watson and I. Whates, Eds.), Robinson, London.

Lloyd's and RAL Space. 2010. Space weather: its impact on Earth and implications for business. [online]. Available at: https://www.lloyds.com/~/media/lloyds/reports/360/360%20space%20weather/7311_lloyds_360_space%20weather_03.pdf

Lloyd's. 2008. Pandemic, potential insurance impacts. [online]. Available at: https://www.lloyds.com/~/media/lloyds/reports/emerging%20risk%20reports/er_pandemic_insuranceimpacts_v2.pdf

Lloyd's. 2010. Behaviour: bear, bull or lemming? [online]. Available at: https://www.lloyds.com/news-and-insight/risk-insight/library/understanding-risk/behaviour-bear-bull-or-lemming

Lloyd's. 2012. Cognition: minding risks. [online.] Available at: https://www.lloyds.com/~/media/Lloyds/Reports/Emerging-Risk-Reports/CognitionFINAL-web.pdf

Lloyd's and AER. 2013. Solar Storm Risk to the North American Electric Grid. [online]. Available at: https://www.lloyds.com/~/media/lloyds/reports/emerging%20risk%20reports/solar%20storm%20risk%20to%20the%20north%20american%20electric%20grid.pdf

Lloyd's. 2015. Lloyd's City Risk Index 2015-2025. [online]. Available at: https://www.lloyds.com/cityriskindex/threats/solar_storm

Lloyd's and Arup. 2017. Future cities: building infrastructure resilience. [online]. Available at: https://www.lloyds.com/~/media/files/news%20and%20insight/risk%20insight/2017/arup/lloyds_arup%20future%20cities%202017.pdf

Los Angeles Times. 2012. 6.6 Sylmar quake almost felled a dam 41 years ago today [online]. Available at: http://latimesblogs.latimes.com/lanow/2012/02/sylmar-earthquake-anniversary-dam-almost-collapse.html

MacMahon, B. 2011. Presentation at CAS Spring Meeting, Palm Beach, Fl. [online]. Available at: https://www.casact.org/education/spring/2011/handouts/C3-MacMahon.pdf

McCurry, J. 2005. Union chief blames bullying rail firm for Japanese train crash. The Guardian, 29 April. [online]. Available at: https://www.theguardian.com/world/2005/apr/29/japan.justinmccurry
Ngwira C.M. et al. 2013. Simulation of the 23 July 2012 extreme space weather event: what if this extremely rare CME was Earth directed? Space Weather, Vol.11, 671-670. [online]. Available at: http://onlinelibrary.wiley.com/doi/10.1002/2013SW000990/abstract

Mercury News. 2017. SFO close-call: Air Canada flight missed planes by 100 feet. [online]. Available at: http://www.mercurynews.com/2017/07/13/canadian-aviation-officials-determine-just-how-close-air-canada-flight-got-to-sfo-airplanes/

Met Office. 2007. Storm surge — November 2007. [online]. Available at: https://www.metoffice.gov.uk/about-us/who/how/case-studies/floods-2007

NASA. 2012. Near Miss: The Solar Superstorm of July 2012. [online]. Available at: https://science.nasa.gov/science-news/science-at-nasa/2014/23jul_superstorm

NASA Goddard Space Flight Center. 2015. Brief outburst [online]. Available at: https://www.flickr.com/photos/gsfc/16760026566/in/photolist-rx2vZh-eSqM1Q-qbM1VD-kvh6cE-dgdouJ-d6mHnY-csBTpY-d5UJF5-6zxYvb-d5UHAf-bxkQBK-bhWC36-d5UHiu-d6x8hh-bhWyqK-oX69UY-egcv1D-eSqM59-bozyiY-cZSu2u-oxuXZL-ef8pJR-b8wsMi-egifLq-d5UJiq-TgMkoH-8q1Lru-bjkTfa-fCpPg5-bN4yf2-boi589-bzakEj-j6mSQZ-efJGiG-bxkQgc-bYzYiS-apCzE2-b8ws4K-dtBfWJ-nMZDYf-dtvHND-dtvHbg-bzbTpS-p7Pc2U-p7Pj1T-nNapsV-p7NeoR-9mHQ6E-bN4yar-9QWhAQ

NASA Goddard Space Flight Center. 2016. Hurricane Matthew hits Haiti. [online]. Available at: https://www.flickr.com/photos/gsfc/30024169472/in/photolist-MK8Hym-MNr3QA-QLJskt-N4jf95-MRDc35-N4j5ty-M9KDC4-MYStUT-N4jaCG-MYSnAR-M9FcoQ-N7p97X-MYSbzH-M9FnaU-MYSJdx-N4joKy-N4jiQ3-Qu8TH7-MYSFBv-M5kFWW-M9Ffr3-MYS2XT-M9KfNg-M9Kxht-N4jARs-N7q4YK-M9JD1p-MEbjHJ-M9KsdF-N4jvsG-N4jDKo-N4jQNA-MYS6gg-MEczhw-N7pFs2-MEcHeU-MEct87-N4k6TW-M9JZKk-MEcGBm-N4kdMW-M9G1Yj-N4k9gb-M9EXdA-MYTgmz-MSuspD-MEco9Q-MEbzjh-M9EQgQ-N7opyv

NBC News, 2014. Costa Concordia Captain Francesco Schettino Testifies at Trial. [online]. Available at: https://www.nbcnews.com/news/world/costa-concordia-captain-francesco-schettino-testifies-trial-n259711

NSCS. 2004. The fight against terror. Singapore National Security Coordination Centre. [online]. Available at: https://www.nscs.gov.sg/public/download.ashx?id=1031

NTSB. 2010. Loss of Thrust in Both Engines After Encountering a Flock of Birds and Subsequent Ditching on the Hudson River US Airways Flight 1549 Airbus A320-214, N106US Weehawken, New Jersey January 15, 2009. Accident Report NTSB/AAR-10/03. [online]. Available at: https://www.ntsb.gov/investigations/AccidentReports/Reports/AAR1003.pdf

Parker, D. 1992. Oakland Office of Fire Services, ed. "The Oakland-Berkeley Hills Fire: An Overview". San Francisco Fire Department : Fire Commission.[online]. Available at: http://www.sfmuseum.org/oakfire/overview.html

PCS. 2017. Re-survey of insured property damage. Catastrophe Bulletin Serial No.1650, January 5.

Pearl, J. 2009. Causality: models, reasoning and inference. Cambridge University Press.

Perrow, C. 1999. Normal accidents. Princeton University Press, Princeton N.J.

Powell, C.F. 1938 The Royal Society expedition to Montserrat, B.W.I., final report. Philos. Trans. Roy. Soc. A., Vol. 237, pp.1-34.

Professional Marine. 2007. Torrey Canyon alerted the world to the dangers that lay ahead. [online] Available at: http://www.professionalmariner.com/March-2007/Torrey-Canyon-alerted-the-world-to-the-dangers-that-lay-ahead/

Prudential Regulatory Authority. 2014. Consultation Paper | CP7/14 Solvency II: calculation of technical provisions and the use of internal models for general insurers. [online]. Available at: http://www.bankofengland.co.uk/pra/Documents/publications/policy/2014/solvency2calctechcp714.pdf

Reason, J. 2008. The human contribution. Ashgate Publishing, Farnham, Surrey.

Reid, R.L. 1986. The psychology of the near miss. J. Gambling Behaviour, Vol.2, pp.32-39.

RMS. 2017. RMS Estimates Hurricane Irma Insured Losses from Wind, Storm Surge and Inland Flood Damage will be Between USD $35 and $55 Billion [online]. Available at: https://www.rms.com/newsroom/press-releases/press-detail/2017-09-20/rms-estimates-hurricane-irma-insured-losses-from-wind-storm-surge-and-inland-flood-damage-will-be-between-usd-35-and-55-billion

Roese, N.J. 1997. Counterfactual thinking. Psychological Bulletin, Vol.121, pp.131-148.

Ruff L., Kanamori H. 1980. Seismicity and the subduction process. Physics of the Earth and Planetary Interiors, 23, 240-252.

Sawai Y., Namegaya Y., Okamura Y., Satake K., Shishikura M. 2012. Challenges of anticipating the 2011 Tohoku earthquake and tsunami using coastal geology. Geophys. Res. Lett., Vol.39, 21309. [online.] Available at: http://earthweb.ess.washington.edu/gomberg/SZOSeminar/Papers/SawaietalGRL12.pdf

Seed H.B., Seed R.B., Harder L.F., Jong H-L. (1989) Re-evaluation of the Lower San Fernando Dam. Examination of the post-earthquake slide of February 9, 1971. U.S. Corps of Engineers Report , GL-89-2. [online]. Available at: http://acwc.sdp.sirsi.net/client/en_US/search/asset/1036303;jsessionid=8BEA8864EA180EF3E2E4B05C92413AED.enterprise-15000

Seria, J. 2016. Exploring alternate realities: counterfactual approaches for extreme loss modelling. The case of the 2016 Alberta Wildfires. [online]. Available at: https://www.actuaries.org.uk/documents/d9-exploring-alternate-realities-counterfactual-analysis-extreme-loss

Shi X. et al. (2017) How complex is the 2016 M7.8 Kaikoura earthquake, South Island, New Zealand? *Science Bulletin*.

Simkin T., Siebert L. 1994. Volcanoes of the world. Smithsonian Institution, Geoscience Press.

Space Shuttle Magazine. 2013. Cause and consequences of the Columbia Space Shuttle Disaster. [online]. Available at: http://www.spacesafetymagazine.com/space-disasters/columbia-disaster/columbia-tragedy-repeated/

Staletovich J. (2017) Irma damage expected to reach $18 billion in the U.S. Miami Herald. 13 September. [online]. Available at: http://www.miamiherald.com/news/weather/hurricane/article173182856.html.

TAIC. 2014. Marine inquiry 11-204. Container ship MV Rena grounding on Astrolabe Reef, 5 October 2011. Final Report. [online]. Available at: http://img.scoop.co.nz/media/pdfs/1412/11204.pdf

Taleb N.N. 2001. Fooled by randomness. Texere publishing, Knutsford.

Taleb, N.N. 2007. The black swan. Random House, New York.

Tetlock, P.E. and Belkin, A. [Eds.]. 1996. Counterfactual thought experiments in world politics. Princeton University Press, Princeton N.J.

The Marine Executive. 2016. Tanker Collides With Container Ship Off Singapore. [online]. Available at: http://maritime-executive.com/article/tanker-collides-with-container-ship-off-singapore

USGS. 2015. Long Term Time Dependent Probabilities for the Third Uniform California Earthquake Rupture Forecast (UCERF3). Bulletin of the Seismological Society of America. [online]. Available at: https://pubs.er.usgs.gov/publication/70147094

Weather Stats. 2017. Wind Direction - Quarterly data seasonal for Fort McMurray. [online]. Available at: https://fortmcmurray.weatherstats.ca/charts/wind_direction-squarterly.html

Willsher, K. Germanwings crash: victims' relatives say Lufthansa should have stopped pilot flying. The guardian, 13 March. [online]. Available at: https://www.theguardian.com/world/2016/mar/13/germanwings-pilot-psychiatrists-two-weeks-before-crash-final-report

Woo, G. 2011. Calculating catastrophe. Imperial College Press, London.

Woo, G. 2016. Counterfactual disaster risk analysis. Variance. Casualty Actuarial Society. Available at: http://www.variancejournal.org/articlespress/articles/Counterfactual-Woo.pdf