Institute of Catastrophe Risk Management

Counterfactual Insurance Disaster Analysis

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ABSTRACT

A statistical foundation of risk analysis is the database of actual insurance loss experience. The past is traditionally treated by both historians and disaster professionals as fixed and immutable. But from a physicist's perspective, history is just one possible realization of what might have happened. A stochastic analysis of the past is an exploratory exercise in counterfactual history, helping reduce surprise at extreme events. The value of counterfactual insurance disaster analysis is illustrated with examples from a diverse range of natural and man-made perils.

1. INTRODUCTION

A statistical foundation of actuarial analysis is the database of actual loss experience. Whenever a catastrophe loss event occurs without apparent historical precedent, insurers may be resigned to learning by costly surprise. The 21st century has spawned a special glossary of terms to describe surprising catastrophes: black swans, dragon kings, unknown unknowns etc.. Risk ambiguity and Knightian uncertainty are often cited to explain the limits of risk analysis and excuse surprise as almost inevitable. But apart from learning a new vocabulary to cover unforeseen catastrophe losses, how might insurers be better prepared to cope with such extreme rare events, and be surprised less?

One avenue of development is to explore the realm of counterfactual history – what might have happened. From a physicist's perspective, history is just one possible realization of what might have happened. But the past is traditionally treated by historians, disaster professionals and insurers as fixed and immutable. Indeed, etymologically, the word *disaster* means an unfavourable aspect of a star; as if the clockwork motions of the stars pre-determined the dates of catastrophes astrologically as precisely as eclipses.

Major surprises may be discovered lurking in alternative realizations of historical experience. A writer of counterfactual fiction, Philip Roth (2004), has noted that 'The terror of the unforeseen is what the science of history hides'. All manner of unforeseen surprising catastrophes were close to occurring, but ultimately did not materialize, and hence are completely absent from the historical record, and therefore remain hidden from view of insurers. The hijacking of a passenger jet just to be flown into an iconic structure might have happened before 9/11; the Algerian terrorist organization GIA attempted to destroy the Eiffel Tower in Paris in this way in 1994. A fundamental paradigm of counterfactual history is that of the near miss: disasters hidden by history because they never quite happened, and just remain mostly forgotten as near misses. At the time of 9/11, very few property underwriters would have been aware of the Eiffel Tower plot, and its implications for aviation risk.

Landslide disaster provides a compelling visual metaphor of all manner of near misses. On 21 January 2014, a landslide in the Alpine village of Ronchi di Termeno in northern Italy sent two giant boulders tumbling downhill towards a 300 year old farmhouse. One boulder, about 160 cubic metres in size, came to rest right against the farmhouse, narrowly missing a vehicle**.** The second boulder smashed all the way through an adjacent barn, missing the farmhouse by less than a metre, and continued rolling before its momentum ran out in a vineyard. Most remarkably, the final vineyard resting place of this massive boulder was actually close to where another huge boulder had come to rest from some previous major rockfall. This old boulder, which apparently had been there for many years, is shown in the foreground of Figure 1. This was tangible evidence of an earlier near miss, so providing warning of the landslide danger, which had gone unheeded. In this case, as often with hazard warnings, psychological relief that a disaster has been averted induced a mental state of risk amnesia and apathy that substituted for effective risk mitigation. Action to eliminate the mountain risk source was only taken after the January 2014 near miss.

Figure 1: A giant boulder came down the Alpine mountain on 21 January 2014, just missing a farmhouse, and stopping just short of where another giant boulder had come to rest years previously. [Photo: Markus Hell, AP]

Fortunately, there were no casualties from this landslide. Two months later, on 23 March 2014 on a hill in Washington State in the northwest United States, a mudslide engulfed the village of Oso and claimed many victims. It was similar to the Steelhead landslide of 25 January 2006, that counterfactually might have killed many and discouraged further home construction, which carried on regardless. The surprised local head of emergency management stated that the 2014 event was a completely unforeseen slide that came out of nowhere.

With the current state of historical and scientific knowledge, there are very few hazard events that should take catastrophe insurers by surprise. Almost all either did happen before in some guise, or, taking a counterfactual view, might well have happened before. Take for example the great tsunami and magnitude 9 earthquake of 11th March 2011. It is doubtful that this was the strongest historical earthquake to have struck Japan. The Sanriku Earthquake of 869 is a strong candidate, as judged by a joint research team of Osaka City University. They found evidence that traces of the tsunami following this 9th century earthquake impacted an extremely wide area including not just two but all three main prefectures of northeast Japan. This large area indicated to these researchers that the earthquake that caused this enormous tsunami might have measured around magnitude 9.

The respected doyen of Japanese seismology, Prof. Kanamori, had estimated the maximum magnitude to be much lower, around 8.2, on the basis of a global comparison of similar tectonic regions. Granted that the 869 tsunami deposit evidence was indirect and circumstantial, there was still a significant likelihood that the magnitude of the 869 earthquake exceeded the hitherto perceived maximum value of 8.2. Furthermore, even if the 869 event magnitude had just been on the borderline of 8.1 or 8.2, there is a counterfactual dynamic argument that future fault slip might potentially exceed whatever it was in 869.

With such counterfactual arguments unregistered, Japanese society was unprepared and the Japanese coastal tsunami defences were inadequate to cope with the massive tsunami of 11 March 2011. The greatest natural disaster of modern times in Japan was amplified by the loss of coolant accident at the Fukushima nuclear plant, which had tsunami defences deterministically designed for a grossly sub-optimal maximal event.

The nuclear industry, in common with all other technological industries, has a substantial database of near misses and close calls (e.g. Hopkins, 2010), from which safety lessons should be learned, if statistics other than actual incidents and casualties are taken into account. In the interest of promoting safety within industry and reducing the prevalence of accidents, near-miss management systems have been advocated by Kleindorfer et al. (2012), following on from studies at the Wharton Business School, including operational risk (Muermann et al., 2002). Regrettably, the warnings afforded by near misses are often disregarded and ignored by insurers.

The greatest US natural disaster and insurance loss of modern times was caused by the storm surge of Hurricane Katrina in August 2005. During Hurricane Katrina, more than half of the three and a half thousand miles of levees that protect Greater New Orleans were damaged, breached, or destroyed. The infrastructure failures observed in the Greater New Orleans area were partly man-made and might have been prevented. A combination of engineering errors and political decisions resulted in an inferior hurricane protection system. In the decade preceding the levee onslaught of Hurricane Katrina, warning of future hurricane disaster for both public officials and insurers came from two near misses of New Orleans: Hurricane Georges in 1998 and Hurricane Ivan in 2004.

For any insured peril, a statistical analysis of actual loss experience is a natural and obvious actuarial starting point for insurance risk management. However, for perils that may be manifested in rare extreme events, the underlying experience data may be far too sparse for reliable application of statistical methods. Furthermore, the absence of losses tends to lead behaviourally to market complacency. Hurricane Alicia in 1983 was the first hurricane to hit the United States mainland since Hurricane Allen in August 1980. The three year interlude between these two storms was the longest quiescent streak since 1932. This inter-event soft period was a period of strong expansion within Lloyd's of London, which welcomed as new members thousands of new individual investors. It was following Hurricane Alicia that the market displayed an anomalous feedback instability notorious as the London market spiral.

The pitfalls of relying on historical losses alone are illustrated by another classic insurance example: California earthquake insurance between 1971 and 1993 (Klüppelberg et al., 1997). The highest loss ratio of claims to premiums was about 130 during this period, which was active in that it did include two major damaging events: the 9 February 1971 San Fernando earthquake in southern California of magnitude 6.6, and the 17 October 1989 Loma Prieta earthquake in northern California of magnitude 6.9. But despite the dataset including these two severe earthquakes, no extreme value statistical analysis could have prepared insurers for the enormous loss ratio of 2273 which resulted from the Northridge earthquake of 17 January 1994. That such an earthquake of magnitude 6.7 should be capable of claiming some local insurance companies among its victims highlights the inadequacy of reliance on historical loss experience alone.

Occurring within a decade of the inception of catastrophe risk modelling, this was one of the seminal disasters to have forged its market development. At the core of catastrophe insurance risk modelling is the introduction of physical structure into the modelling process. There is very much more knowledge about earthquake risk than the particular set of realized historical losses. This seismological and earthquake engineering knowledge is embedded within a stochastic set of possible future earthquake scenarios, each of which is assigned an annual frequency.

Even if advised of alarming loss outcomes of an ensemble of future stochastic event scenarios, insurance market sentiment is heavily weighted by actual loss experience itself. As social psychologists would appreciate, more weight is given by insurers to what has actually happened in the past, than what hypothetically might happen in the future. Counterfactual analysis of past events should be rather less susceptible to human bias, since it is basically rooted in what has happened before.

An issue often raised about catastrophe modelling is the degree of completeness of the stochastic set of future scenarios, and how much scope there remains for surprises. It is argued here that insurance risk managers would be less exposed to potential surprise over future insurance loss outcomes if a counterfactual stochastic analysis were undertaken of the past, rather than treating historical events as deterministic and past loss experience as immutable data. Illustrations will be drawn from a range of catastrophe insurance markets.

2. SYSTEM STATE REPRESENTATION

Whereas scientists are interested in all event phenomena, insurers are specifically concerned with that subset of events that cause losses. Catastrophe modelling focuses on the probability of an event occurring, and the conditional loss probability given an event occurrence. On its own, this can be rather a superficial phenomenological description. More fundamentally, the risk state of the whole dynamical system can be represented by a set S of *n* underlying natural and human risk variables, some of which are physical or geographical, and some relate to organizational system defence and control: $S = \{X(1), X(2)....X(n)\}$.

At various times *t*, a particular domain, $\boldsymbol{D(t)}$, of the space of underlying risk variables becomes immediately dangerous to an insurance risk portfolio in that the hazard state changes in latency from passive to active, and some external agent of physical force strikes the portfolio. Such an agent might be earthquake ground shaking, volcanic pyroclastic flow, landslide debris flow, wind pressure of a tropical cyclone or tornado, water breach of a flood or tsunami defence, toxic release from an industrial installation, or a terrorist bomb blast.

As observed by an insurer at his office desk, a hazard event occurs at time ***t*** causing loss $\boldsymbol{L(t)}$ to the insured portfolio. From an actuarial perspective, the historical time series of occasional losses $\boldsymbol{L(t)}$ can be analysed by a battery of statistical techniques. However, given the rarity of extreme catastrophe insurance losses, and the sparseness of the loss time series, any statistical analysis just relying on loss experience is fraught with huge uncertainty, the size of which is well appreciated by actuaries and is a source of anxiety (Nicholson et al., 2013). Indeed, it has often been stated of US terrorism insurance risk that it is impossible to estimate the frequency since 9/11 because of the almost total absence of actual insurance loss experience. According to the American Insurance Institute, terrorism risk is uninsurable without government support through the Terrorism Risk Insurance Act.

Fortunately, loss statistics are far from being the only source of useful information and knowledge about a hazard. Indeed, it is the catastrophe modeller's responsibility to understand, measure and chart the extent of the dangerous domain of risk variables $D(t)$. In particular, there are combinations of the input variables $\{X(1), X(2)....X(n)\}$ which lie just outside this dangerous domain, but which may be dynamically perturbed to fall within the dangerous domain (see Fig.2). Relaxation of safety and risk management controls augment the perturbative impact of any reduction in physical safety distance.

The future stochastic event datasets constructed within catastrophe risk models explore and chart the dangerous domain $\boldsymbol{D(t)}$ of risk variables. However, it is not customary for catastrophe modellers to attempt to undertake stochastic modelling of past historical events, which are treated as fixed inflexible data. Gauging the uncertainty in estimating the insurance loss of any event is an important task intrinsic to catastrophe modelling, but not undertaking a stochastic analysis of the event itself.

But interesting insights into the dangerous domain of risk variables, $\boldsymbol{D(t)}$ can be gained from revisiting and rewriting virtual history (Ferguson, 2000). In particular, salutary lessons may be learned from the counterfactual insurance losses that were narrowly averted or diminished because of the haphazard absence of the necessary dynamic perturbations to near miss events.

Insights into the geometrical configuration of the dangerous domain emerge from considering the circumstances in which organizational system defence and controls manage to counter the reducing physical safety distance of a physical hazard variable, and create a resilient response to the threat of casualties and property loss. Marginal parameter variations that significantly amplify catastrophe loss are important to tabulate and chart. There are numerous sources of nonlinear loss amplification, corresponding to tipping points in hazard, vulnerability and loss aggregation.

A wide range of natural and man-made catastrophes could be taken to illustrate the principles. With respect to wildfire risk, for example, the number of fire ignitions is a crucial risk parameter. In the 1991 East Bay Hills, California, wildfire storm, the fire started on 19 October, and by nightfall was being brought under control. However, a new ignition the following morning rapidly spread the wind-driven fire, overwhelming local and regional fire-fighting crews. More than 3,800 homes were destroyed and 25 people were killed.

The FEMA report (1991) on the wildfire noted candidly that '*the most significant factor that should be recognized from this incident is that the fire was beyond the capability of fire suppression forces to control*.

The stage was set by a number of contributing factors that created the opportunity for disaster. When the Santa Ana wind condition was added to those risk factors, the combination was more than any fire department could handle.

It was remarked by one fire official that if the same fire risk factors had been present in a park or forest, the area would have been closed to all activities. As long as the wind was present, the fire was going to continue to spread, no matter what strategy and tactics were used and no matter how much equipment and how many firefighters were there to try to stop it. The fire was contained only when the wind changed'.

A counterfactual analysis of this major US wildfire insurance disaster is especially illuminating for what it indicates for an estimate of wildfire Probable Maximum Loss. A runaway disaster might have ensued through a 'perfect storm' combination of three risk variables $X(1), X(2), X(3)$: persistent hot dry northeasterly winds; fresh ignitions, (either accidentally or maliciously generated); fire-fighting crew fatigue and resource restrictions.

Identification of comparable 'perfect storm' counterfactual analyses for historical realizations of other perils would reduce the prospect for surprise at future catastrophe insurance loss. Extreme persistent rainfall can greatly exacerbate flood insurance loss, as shown by the Central Europe floods of August 2002. A combination of sustained low pressure and comparatively high summer temperatures were the key risk variables that generated the meteorological conditions for a fountain of water deluging multiple European states, without heed of national borders. For other major historical catastrophe insurance events, much would be gained, both intellectually and financially, from the identification of the key risk variables that would have worsened still further the degree of insurance loss.

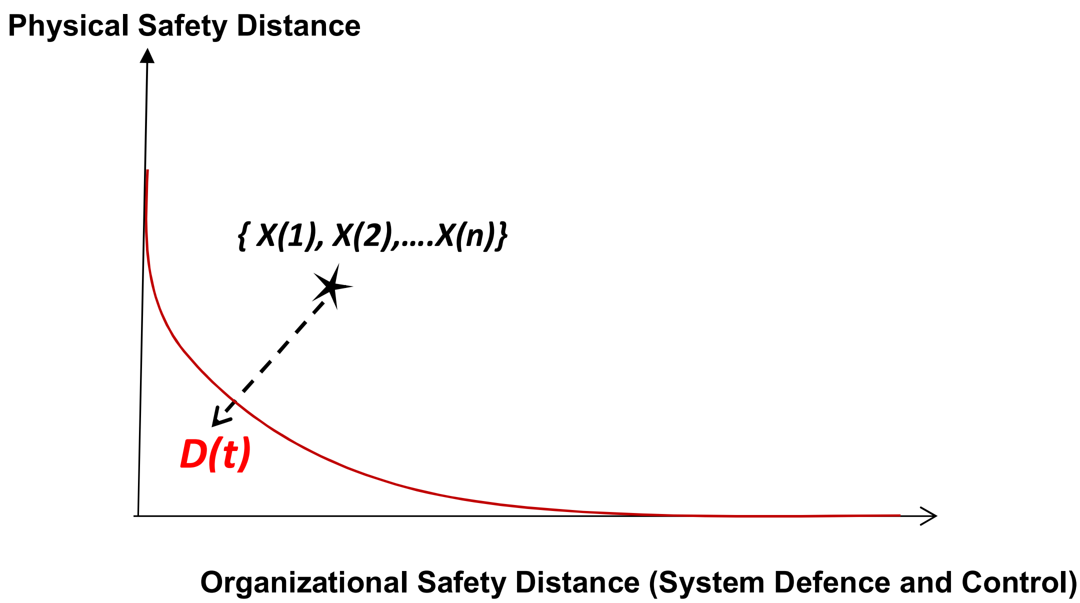

Figure 2: Perturbation of a system state into the dangerous domain D(t), through attrition of the physical and organizational safety distances

Part of the risk management value of counterfactual disaster analysis is the capacity to identify prospects for future disasters, even where the historical evidence is very sparse or completely non-existent. There are numerous examples in public transportation by land, air and sea. They provide some of the most graphic and hair-raising near miss scenarios. In attempting to land at Heathrow in thick fog on 21 November 1989, a Boeing 747 missed the roof of a local airport hotel by a clearance distance of just twelve feet (Macrae, 2010).

Take the more recent maritime insurance example of the Costa Concordia cruise ship which sailed up the northwest coast of Italy, past the island of Giglio (see Fig. 3). One of the key hazard variables determining the ship's hazard state was its distance (in kilometres) from the navigational safety contour around the island. This might be designated, without loss of generality, as $X(1)$. The official scheduled route of the cruise ship gave the island an abundantly wide berth, $X(1) > 10$ kilometres. Given the terrestrial accuracy of GPS expressed within metres, the dangerous domain should never have been close to being breached, even allowing for gross human navigational error.

However, a tradition had developed for the Costa Concordia to be steered *intentionally* very close to the safety contour to maximize the spectacle for islanders and cruise ship passengers alike - so that $X(1) \sim 0$. This then left virtually no margin for the navigational failings that would take the Costa Concordia within the dangerous sinking domain, as happened on the fateful evening on 13 January 2012. With the burgeoning costs of the lengthy engineering salvage operation, this became the worst maritime insurance loss, exceeding $2 billion. A counterfactual analysis would have warned of the risk of such a catastrophe loss.

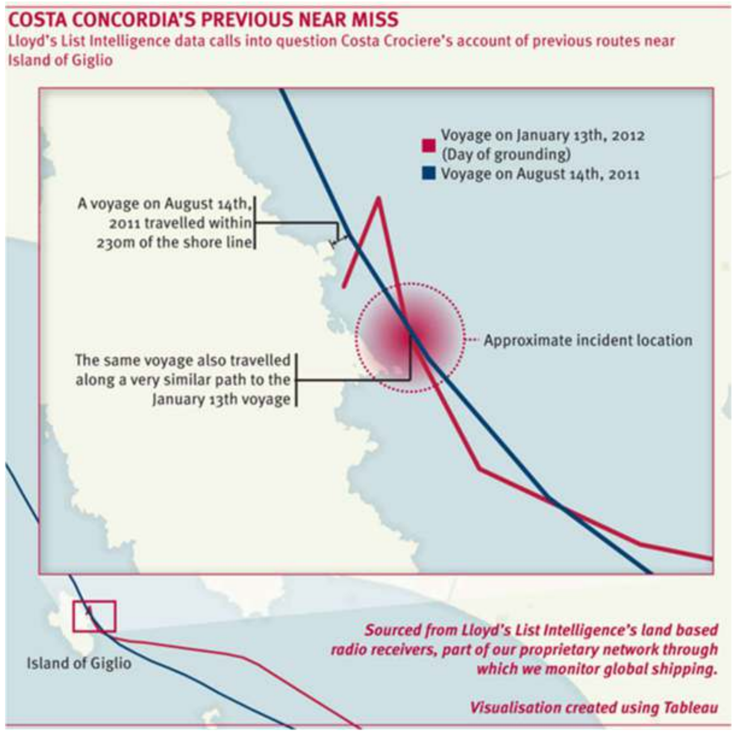

Figure 3: Track detours near the island of Giglio of the Costa Concordia on 13 January 2012 and 14 August, 2011, based on Lloyd's List maritime intelligence data.

This catastrophe insurance loss was man-made. The detour was intentional, even if the grounding of the cruise ship was not. Consider next an intentional man-made disaster, caused by terrorists. On 26 February 1993, there was a terrorist vehicle bomb attack on the New York World Trade Center. The WTC shook violently but did not collapse. But it was a near miss. According to courtroom evidence of the WTC's architect, corroborated by an FBI explosives expert, if the van had been left closer to the poured concrete foundations, the terrorists would have succeeded in causing tower collapse. Peripheral damage to adjacent buildings would then have also been substantial.

As it was, the 1993 terrorist bombing of the WTC shut down Tower 1 for six weeks and Tower 2 for four weeks. The total insurance loss, including property and equipment damage and loss of revenue, was about $500 million; approximately two orders of magnitude less than that caused by the Al Qaeda terrorist attack on 9/11, masterminded by the uncle of Ramsi Yousef, the 1993 bomber. Defining as the distance of the terrorist van bomb from the optimal location for causing building collapse, a comparatively minor perturbation to the terrorist plot could have gained the extra leverage in force-impact ratio that is a hallmark of terrorism modus operandi, and would have greatly amplified the insurance loss to catastrophic proportions. Explicit counterfactual disaster analysis of the 1993 attack would have better prepared the terrorism insurance market, both in respect of underwriting and risk management, for the horrific losses of 9/11, which established terrorism as a US catastrophe insurance peril for the first time – the actual 1993 loss fell below the catastrophe threshold.

3. COUNTERFACTUAL STOCHASTIC SIMULATION OF THE PAST

Stochastic simulations are routinely done for the future, but rarely for the past. However, there are important risk management lessons to be learned from exploring alternative realizations of virtual history, especially understanding the degree of loss variability of past events. Regarding past losses as determinate without stochastic analysis of historical loss variability, the potential scale of variability in future loss projections could take insurers by surprise. There is a substantial epistemic component due to lack of reliable information about building vulnerability, and insufficient knowledge of failure engineering, as was the case with the 1994 Northridge earthquake. But insurers also need to be reminded that there is also a significant aleatory component to loss due to the sheer randomness of events.

As a salient example of how a minor random perturbation to the system state can have a massive impact on insured loss, the case study of the Al Qaeda attack on the In-Amenas gas plant in Algeria in January 2013 is particularly notable. A stray terrorist bullet accidentally caused a power blackout that automatically shut down the plant (Statoil, 2013). This was a stroke of good fortune because it prevented the terrorists from achieving their goal of setting off a massive gas explosion on site. This event is since known for being a hostage crisis, but, counterfactually, it could have been a massive petrochemical disaster as well. In this example, the status of the on-site power supply was a crucial state hazard variable governing the scale of loss. By lucky accident, this hazard variable was set to the safe value through random terrorist action itself.

This case study illustrates a key principle. Even though the multi-dimensional space of n risk variables $X(1), X(2)....X(n)$ has a complex multivariate topology, important insight can be gained from the marginal variation of individual or several variables. Thus the binary switch of on-site power could leverage loss at a petrochemical plant by orders of magnitude. Power-outage is well appreciated to be a key variable for estimating the scale of business interruption, especially where industries lack supply chain resilience against external hazards. Power loss was a major factor impeding the 24 hour production schedule of computer microchips after the Chi-Chi earthquake in Taiwan of 21 September 1999 (RMS, 1999).

In the realm of meteorological loss amplifiers, a notable marginal variable is the state of the tide. Consider coastal flooding. The state of the tide is a key variable for coastal flooding from a storm surge or tsunami. Overtopping of a coastal sea defence defines a key boundary of the dangerous domain. The historical record provides numerous examples of calamitous coastal flooding being averted, or the insurance loss severity being considerably mitigated, by a combination of stout sea defences – and luck that the highest hazard level did not coincide with high tide. In October 2012, Superstorm Sandy struck Boston at low tide, but up to 6% of Boston could have been flooded if Sandy had arrived at high tide (Douglas et al., 2013). Four months later, a four-foot storm surge hit Boston, fortunately again 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.

As an illustration of the value of structured physical modelling to elucidate the characteristics of the dangerous domain $D(t)$, consider the problem of calculating probabilistic risk curves for the overtopping of coastal sea defences. This hydrodynamic modelling exercise needs to be addressed taking account of dynamic interactions between the tide and the external forcing variable, which may be a storm surge or tsunami (Kowalik et al., 2010).

The use of statistical resampling methods, such as the bootstrap, for estimating uncertainty in extreme value analysis of hurricanes and other weather hazards was advocated in 2003 by Coles and Simiu. But no amount of resampling of the hurricane wind speed database before 2005 could have forewarned of the catastrophe insurance loss of Hurricane Katrina in August 2005. On the hand, a counterfactual analysis of hurricanes Georges in 1998 and Ivan in 2004 would have been more effective in preparing insurers for the record-breaking losses to come. As such, counterfactual analysis of historical events is an important supplementary tool for uncertainty assessment.

3.1 EARTHQUAKE HAZARD

There are so many random aleatory components to earthquake hazard that perhaps it is unsurprising that some communities in seismic zones have developed a fatalistic attitude towards earthquake danger. Take time of day, for example. This is a crucial parameter governing the casualty rate in earthquakes, and therefore workers compensation insurance. It is well known that fatalities in the two most recent destructive earthquakes in northern and southern California have been remarkably light. Fortuitously, the Loma Prieta earthquake of 17 October 1989 occurred at 5pm, during warm-up for the baseball World Series. Baseball fans who were watching on television might otherwise have been endangered in offices or on the freeways that collapsed. Likewise, offices and freeways in the Los Angeles area were mostly empty when the Northridge earthquake of 17 January 1994 struck early in the morning at 4.30am.

Another important hazard variable X for earthquake insurers is the location of rupture initiation on a major active fault. In probabilistic seismic hazard analysis, this variable is typically represented as uniformly distributed along the fault length. This is a geographic variable that has a substantial influence on the spatial footprint of strong ground motion, and hence on the insurance loss of a portfolio located in and around this footprint. This is exemplified by the first major international earthquake catastrophe insurance loss: the great San Francisco earthquake and fire of 18 April 1906. Severe as the insurance loss was, fortunately for the earthquake insurers - and perhaps for the future of the global earthquake insurance market - the loss was not nearly as bad as a counterfactual analysis indicates it might have been.

The 1906 event was 'the Big One', but, as shown on the left of Fig. 4, the red zone of strongest shaking was away from the city of San Francisco, close to the rupture initiation point, marked by a star in Fig. 4. Fortunately, the shaking in 1906 in San Francisco was relatively weak compared to what might have been. Much worse would have been 'The Bad One', as illustrated on the right of Fig. 4, where the rupture might have initiated at the northern end of the San Andreas Fault, and propagated southeastwards towards the San Francisco Bay area, focusing seismic wave energy in a red zone of especially high risk accumulation.

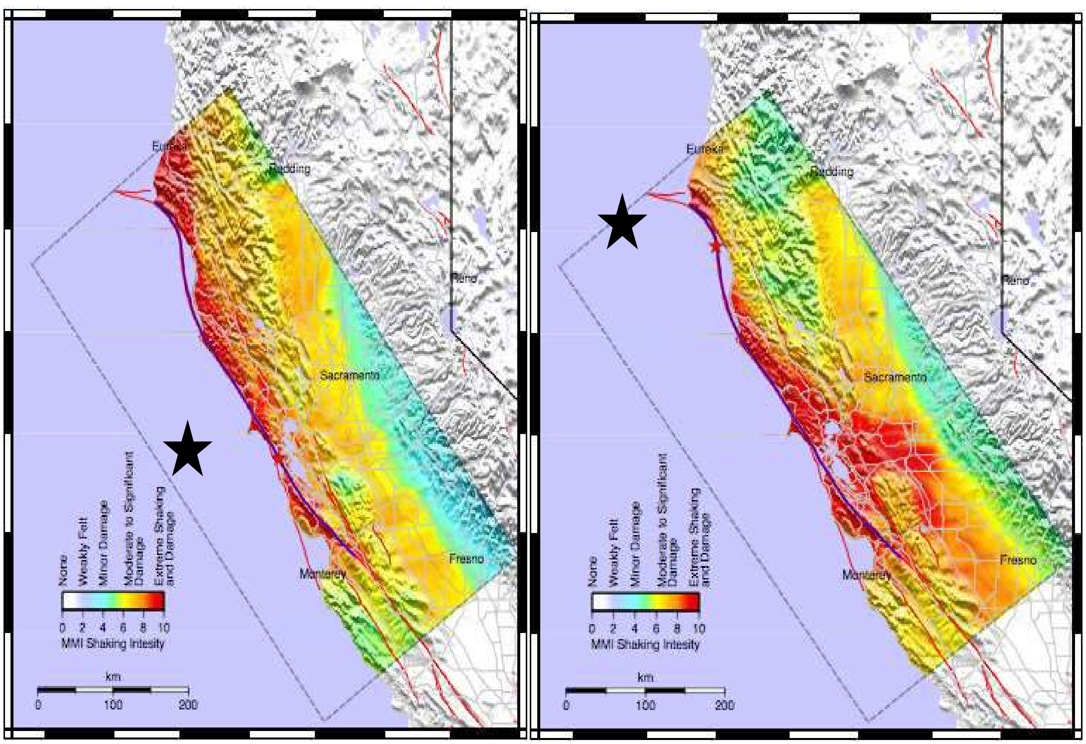

Figure 4: Contrast in damage patterns for two earthquake scenarios ['The Big One' at the left; 'The Bad One' at the right] on the San Andreas Fault, as mapped by the US Geological Survey. The red zone suffers extreme ground shaking and damage. Black stars indicate the initiation point of the fault rupture.

There are other counterfactuals that are important for earthquake insurers to comprehend. Consider a situation where a major metropolis is situated within an active fault zone. Seismological studies of past regional earthquakes may provide evidence that the associated fault rupture from a previous regional earthquake stopped well short of this metropolis. But instead of complacency over the seismic safety of the metropolis, a counterfactual attitude towards this historical near miss would be to focus attention on managing the risk associated with an extension of the fault rupture zone towards the metropolis.

A significant catastrophe insurance example is the devastation of the city centre of Christchurch, New Zealand, by a magnitude 6.3 earthquake on 22 February 2011, that was likely dynamically triggered by the larger magnitude 7.1 Darfield, Canterbury, earthquake of 4 September 2010. The specific characteristics of the seismological connection between these two major South Island events, in particular whether the latter earthquake might be considered an aftershock of the former, was not only a matter of dispute within the seismological community, but also became a highly contentious issue of reinsurance law.

3.2 INTERDICTION OF TERRORIST PLOTS

A salutary risk management lesson that may be learned by insurers from a counterfactual disaster analysis is how fortunate they may have been to have survived a number of near misses without incurring a significant loss. US terrorism risk in the decade after 9/11 is instructive in this respect. In the countries of the western alliance, counter-terrorism and intelligence capabilities are very strong, and surveillance of terrorist activities is extremely wide-ranging, intensive and indiscriminate, as the former intelligence staff member Edward Snowden has publicly revealed. Accordingly, in the western alliance, terrorists cannot attack at will, and the great majority of terrorist plots are interdicted, so substantially mitigating the terrorism insurance risk.

For the man-made peril of terrorism in Europe and North America, one of the most important hazard variables is the interdiction rate of terrorist plots. This interdiction rate is a function of the plot size, as gauged by the number of operatives involved (Woo, 2011). The more operatives involved in a plot, the greater is the chance that one of them will be placed under individual surveillance. The security services track the contacts of known or suspected terrorists. In spider-web fashion, they also track the contacts of these contacts etc.. Social network analysis of surveillance webs indicates a high probability of about 95% that any ambitious plot involving ten operatives would be interdicted. This is consistent with the injunction from Osama bin Laden in Abottabad that plots against the US homeland should involve at most ten operatives.

In the decade after 9/11, there were thirty significant US terrorist plots confirmed by courtroom convictions. For each of these plots, the chance of the plot being interdicted can be calculated from the number of operatives involved. Contingent on a plot evading interdiction, the likelihood of the plot succeeding technically to cause insurance loss can then be estimated. Summing over the thirty confirmed plots, a counterfactual estimate of the expected number of loss-generating plots during this decade is about four. US terrorism insurers contemplating their benign underwriting experience over this decade should not forget the three terrorists in maximum security prisons who nearly caused catastrophe insurance loss: the airline shoe-bomber, Richard Reid, in 2001, the airline underpants bomber, Umar Farouk Abdulmutallab, in 2009, as well as the Times Square vehicle bomber, Faisal Shahzad, in 2010. Counterfactually, with better trade-craft, modest changes to the ignition systems of these improvised explosive devices could have amplified insurance losses to catastrophe proportions.

3.3 VOLCANIC UNREST

In volcano catalogues of eruptions, it has not been routine practice to include periods of unrest. These are times when scientific observations have been made of some external signs of activity, other than eruptive activity itself. Observations of unrest might include volcanic tremor, gas emissions, and inflation of the flanks of the volcano. This incompleteness of information reflects the traditional perception that such data are of scientific interest, but rather inessential for hazard estimation, which is primarily dependent on the geological and historical time series of the actual eruption events themselves.

However, most volcanoes have a low frequency of eruption, and such periods of unrest are important indicators of failed eruptions which should be taken into account in volcano hazard assessment. If periods of unrest are not adequately documented or taken into account, volcano hazard assessment may be warped by the absence of eruptive activity for hundreds or even thousands of years, which may give a misleading impression to insurers and civil protection authorities alike that the volcano is in a quiescent and safe dormant state.

Soufrière Hills in Montserrat is a prime example of a volcano which, until 1995, had not erupted for almost four hundred years, yet had given rise to three periods of significant unrest over the previous century. These might be interpreted as failed attempts at eruption, and might have been recognized as such in volcano risk assessments for general public planning purposes, as well by insurers. As it was, the government of Montserrat granted land on a hazard-prone site for a medical school campus of the American University of the Caribbean. Classes started in 1980, were interrupted by Hurricane Hugo in 1989, and closed six years later when the volcano erupted.

Key system state variables for volcano hazard include those governing the subterranean dynamics, e.g. the influx of magma into the magma chamber feeding the volcano. Periods of unrest may correspond to intermittent intrusions of magma which are insufficient to lead to eruptive activity. Symptoms of unrest may be detected from scientific monitoring of the underlying geophysical, geochemical and geodetic causal factors. This evidence can then be processed probabilistically, incorporating expert judgements, using a Bayesian Belief Network framework (Hincks et al., 2014).

For the i'th historical period of unrest , a Bayesian Belief Network can generate an estimate of the counterfactual likelihood that the unrest might lead to an eruption . With these likelihoods evaluated, the annual probability of an eruption can be calculated in terms of the duration covering all the unrest periods as:

$$\Pr(E) = \sum_i \Pr(E \mid U_i) / T$$

For Montserrat, the duration T is the century from 1890 to 1990, during which there were three distinct episodes of unrest in the 1890s, 1930s and 1960s. Based on the information available, the likelihood summation over the three unrest episodes is approximately 1. Hence a baseline annual eruption frequency would thus have been about 1%, which is higher than using the elapsed time to the last eruption in 1630. Accordingly, this approach would have yielded a more pessimistic, but ultimately more realistic, assessment of volcanic hazard at the island capital Plymouth, which was destroyed by a pyroclastic flow in 1997.

In the authoritative Smithsonian Institution catalogue of volcanoes of the world (Simkins et al., 1994), which was published shortly before the eruption in 1995, the 1630 eruption is included as the sole entry for Montserrat - but none of the unrest history is listed. A counterfactual analysis of this unrest history would have been very instructive for insurers of property on this volcanic Caribbean island, and might have helped avert acrimonious insurance dispute in the law courts over whether the surprising volcanic eruption might be considered, with a rather oblique interpretation of insurance contract language, as an 'explosion'.

4. COUNTERFACTUAL PERSPECTIVE ON UK NATURAL HAZARDS

The 2014 southern England floods, associated with the wettest winter in England and Wales for almost 250 years, illustrate how a single hazard variable, namely the prolonged and sustained duration of rainfall, can cause a system to move into a state deep within the danger domain. Flow rates on the River Thames remained exceptionally high for longer than in any previous flood episode since 1883. Correspondingly, floodplain inundations were extensive and protracted (Met Office, 2014).

The clustering and persistence of the winter storms was highly unusual. A rare tipping point was reached with the consequent saturation of the ground, whereafter even when there was a lull in the rainfall, the flood waters did not recede much and some properties remained flooded for many weeks. Such tipping points are dangerous insurance loss amplifiers. Identifying them well in advance is a principal objective of counterfactual insurance disaster analysis. For coastal flood risk associated with storm surges arriving on a high tide, failure of key sea defences is a major insurance loss tipping point.

The windstorm on 4 and 5 December 2013 generated a major North Sea storm surge, which coincided with one of the highest tides of the year and threatened much of the East coast in a similar way to the destructive 1953 flood, which claimed 307 lives in English coastal towns. However, with improved coastal defences, major damage was avoided. Crucially, the Thames Barrier was successfully raised to protect London from the largest tide ever recorded at Southend. Counterfactually, technical inoperability of the Thames Barrier would have caused disastrous flood loss within the city of London, which otherwise escaped the inundation havoc in neighbouring districts.

A tipping point in health risk can arise from the occasional confluence of two independent risk factors. As a natural hazard affecting the health of the UK population, a sustained volcanic eruption in Iceland, generating vast quantities of toxic gases, can have serious consequences for those with respiratory problems. The Laki eruption in Iceland of 1783 lasted eight months, during which about 14 cubic metres of lava were erupted. The resulting acid fog dispersed over Europe caused more than 10,000 excess deaths in England. But it could have been much worse. In the previous year, 1782, a pandemic originating in China spread westwards, through Germany into England and Scotland. Had the pandemic occurred a year later, (or Laki erupted a year earlier), the combination of influenza and acid fog would have leveraged the death toll to catastrophic levels. This counterfactual 'perfect storm' scenario almost happened with the arrival of the swine flu pandemic from Mexico in 2009. Had it occurred a year later, it would have coincided with the eruption of the Iceland volcano Eyjafjallajōkull in 2010, the ash cloud from which closed down UK airspace for days.

5. EMERGING CATASTROPHE INSURANCE RISKS

Emerging insurance markets, such as in Asia, introduce emerging catastrophe insurance risks. The 2011 Thailand floods generated insurance losses in excess of $10 billion, which came as a financial shock and surprise to the developing Asian insurance market. At the time, catastrophe insurance modelling for Thailand flood was still rather rudimentary. Nevertheless, in estimating Probable Maximum Loss, it is always possible to undertake an exploratory search for risk variables that have the capacity to leverage losses greatly. The discharge of water from dam reservoirs defines an almost literal tipping point for the amplification of catastrophe insurance loss in Thailand. This might have been foreseen from a counterfactual perspective.

Actual loss experience has always been the foundation for actuarial risk analysis. Where losses are frequent, e.g. motor insurance claims, the actual database of losses is large enough to encompass most of the domain of realistic possibility. Risk insights can then be gained through extensive statistical data mining. However, especially for emerging catastrophe insurance risks, actual catastrophe loss experience, especially when it has been light or even non-existent, may be very misleading, and expose underwriters to risk perception bias.

There is an intrinsic insurance market optimism bias which leads insurers to underestimate risks if large losses have not yet materialized. Such social psychological behaviour is explained by market dynamics. The market players who are particularly optimistic that a low loss regime will prevail will tend to have increasing market share. As a consequence of optimism bias, when a catastrophe loss does occur, the market is often taken by surprise. The degree of surprise would be lessened if emerging risks were tracked early and managed well in advance of any catastrophe event. Counterfactual analysis of emerging risks would be helpful in this tracking and risk management process. To enlarge the historical event dataset of emerging risks, a stochastic analysis of historical events can be undertaken to explore the range of possible losses that might have arisen.

Such analysis is already instructive for assessing terrorism risk. But it could also be applied in allied insurance domains such as riot and cyber risk. Criminals other than terrorists launch cyber attacks. Cyber risk is an emerging global risk which has yet to cause a catastrophic property insurance loss, although the possibilities are both numerous and worrying. Through cyber action, for example, Internet-enabled Supervisory Control and Data Acquisition (SCADA) systems could be sabotaged, leading to fires and explosions in industrial facilities. According to a Symantec report (Wueest, 2014), companies in the energy sector are facing a growing risk of having their services interrupted or losing data. The threat to energy firms is likely to increase in the coming years as new developments, such as further extensions of smart grids and smart metering expose more infrastructure to the Internet.

The lurking prospect of a SCADA disaster has already existed for a decade. At the beginning of 2003, a marine terminal in Venezuela was targeted by a sabotage attack (Wueest, 2014). During the strike, an attacking group managed to get access to the SCADA network of the oil tanker loading machinery and overwrote programmable logic controllers (PLCs) with an empty program module. This halted machinery, preventing oil tankers from loading for eight hours until the unaffected backup code was reinstalled on the PLCs. The attack was fortunately not too sophisticated, as it was easily spotted. Counterfactually, a small modification of the PLC code instead would probably have gone unnoticed for a long time, and caused substantial damage and business disruption.

Liability risk is another emerging catastrophe insurance risk where counterfactual analysis of historical events can elucidate loss potential and improve risk quantification. Stochastic simulation of past liability loss events would help benchmark and refine the capability of early warning tools developed for catastrophe liability insurance. As an example of marginal parameter variation, delay in ordering product recalls early is a risk parameter that can amplify losses enormously. In 2014, GM finally ordered a recall of older compact cars over an ignition switch problem that was suspected as much as ten years earlier. From mechanical failures to health and environmental problems, counterfactual analysis of earlier incidents provides insurers with additional insights beyond the narrow bounds of actual loss experience.

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