Journal of the Operational Research Society (2013) 64, 638–653 0160-5682/13

www.palgrave-journals.com/jors/

Managing the social amplification of risk: a simulation of interacting actors

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A central problem in managing risk is dealing with social processes that either exaggerate or understate it. A longstanding approach to understanding such processes has been the social amplification of risk framework. But this implies that some true level of risk becomes distorted in social actors' perceptions. Many risk events are characterised by such uncertainties, disagreements and changes in scientific knowledge that it becomes unreasonable to speak of a true level of risk. The most we can often say in such cases is that different groups believe each other to be either amplifying or attenuating a risk. This inherent subjectivity raises the question as to whether risk managers can expect any particular kinds of outcome to emerge. This question is the basis for a case study of zoonotic disease outbreaks using systems dynamics as a modelling medium. The model shows that processes suggested in the social amplification of risk framework produce polarised risk responses among different actors, but that the subjectivity magnifies this polarisation considerably. As this subjectivity takes more complex forms it leaves problematic residues at the end of a disease outbreak, such as an indefinite drop in economic activity and an indefinite increase in anxiety.

Journal of the Operational Research Society (2013) **64,** 638–653. doi:10.1057/jors.2012.80
Published online 11 July 2012

Keywords: social amplification of risk framework; zoonosis; risk perception; risk management; system dynamics; simulation

Introduction

Recent events such as the outbreaks in the UK of highly pathogenic avian influenza illustrate the increasing importance of managing not just the physical development of a hazard but also the social response. The management of hazard becomes the management of 'issues', where public anxiety is regarded less as a peripheral nuisance and more as a legitimate and consequential element of the problem (Leiss, 2001). It therefore becomes as important to model the public perception of risk as it does to model the physical hazard—to understand the spread of concern as much as the spread of a disease, for example. In many cases the perception of risk becomes intimately combined with the physical development of a risk, as beliefs about what is risky behaviour come to influence levels of that behaviour and thereby levels of exposure.

One of the main theoretical tools we have had to explain and predict public risk perception is the social amplification of risk framework due to Kasperson *et al* (1988). As we explain below, this framework claims that social processes often combine to either exaggerate or underplay the risk events experienced by a society. This results in unreasonable and disproportionate reactions to risks, not only among the lay public but also among legislators and others responsible for managing risk. But since its inception the idea of a 'real', objective process of social risk amplification has been questioned (Rayner, 1988; Rip, 1988) and, although work in risk studies and risk management continues to use the concept, it has remained problematic. The question is whether, if we lose the notion of some true risk being distorted by a social process, we lose all ability to anticipate and explain perplexing social responses to a risk event in a way that is informative to policymakers.

We explore this question in the context of risks surrounding the outbreaks of zoonotic diseases—that is, diseases that cross the species barrier to humans from other animals. Recent cases of zoonotic disease, such as BSE, SARS, West Nile virus and highly pathogenic avian influenza (HPAI), have been some of the most highly publicised and controversial risk issues encountered in recent times. Many human diseases are zoonotic in origin but in cases such as BSE and HPAI the disease reservoirs remain in the animal population. This means that a public health risk is bound up with risk to animal welfare, and often risk to the agricultural economy, to food supply chains and to wildlife.

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This in turn produces difficult problems for risk managers and policymakers, who typically want to avoid a general public amplifying the risk and boycotting an industry and its products, but also want to avoid an industry underestimating a risk and failing to practice adequate biosecurity. The BSE case in particular has been associated with ideas about risk amplification (eg, Eldridge and Reilly, 2003) and continues to appear in the literature (Lewis and Tyshenko, 2009). Other zoonoses, such as chronic wasting disease in deer herds, have also been seen as recent objects of risk amplification (Heberlein and Stedman, 2009).

In terms of the social reaction, not all zoonoses are alike. Endemic zoonoses like *E. coli* 157 do periodically receive public attention—for example following outbreaks at open farms and in food supply chains. But it is the more exotic zoonoses like BSE and HPAI that are more clearly associated with undue anxiety and ideas about social risk amplification. Yet these cases also showed how uncertain the best, expertly assessed, supposedly objective risk level can be, and this makes it very problematic to retain the idea of an objective process of social risk amplification. Such cases are therefore an important and promising setting for exploring the idea that amplification is only in the heads of social actors, and for exploring the notion that this might nonetheless produce observable, and potentially highly consequential, outcomes in a way that risk managers need to understand.

Our study involved two main elements, the second of which is the main subject of this article:

1. Exploratory fieldwork to examine how various groups perceived risks and risk amplification in connection with zoonoses like the avian influenza outbreaks in 2007;
2. A systems dynamics simulation to work out what outcomes would emerge in a system of social actors who attributed amplification to other actors.

In the remainder of the paper we first outline the fieldwork and its outcomes, and then describe the model and simulation. Although the article concentrates on the latter, the two parts provide complementary elements of a process of theorising (Kopainsky and Luna-Reyes, 2008): the fieldwork, subjected to grounded analysis, produces a small number of propositions that are built into the systems dynamics model, and the model both operationalises these propositions and explores their consequences when operationalised in this way. The modelling is a basis for developing theory that is relevant to policy and decision making, rather than supporting a specific decision directly. A discussion and conclusion follow.

Literature

Traditionally, the most problematic aspect of public risk perception has been seen as its sometimes dramatic divergence from expert assessments—and the way in which this divergence has been seen as an obstacle both to managing risks specifically and to introducing new technology more generally. This has produced a long-standing interest in the individual perception of risk (eg, Slovic, 1987) and in the way that culture selects particular risks for our attention (eg, Douglas and Wildavsky, 1982). It has led to a strong interest in risk communication (eg, Otway and Wynne, 1989). And it has been a central theme in the social amplification of risk framework (or SARF) that emerged in the late 1980s (Kasperson *et al*, 1988).

The notion behind social risk amplification, developed in a series of articles (Kasperson *et al*, 1988; Renn, 1991; Burns *et al*, 1993; Kasperson and Kasperson, 1996), is that a risk event produces signals that are processed and sometimes amplified by a succession of social actors behaving as communication ‘stations’. They interact and observe each other’s responses, sometimes producing considerable amplification of the original signal. A consequence is that there are often several secondary effects, such as product boycotts or losses of institutional trust, that compound the effect of the original risk event. A substantial amount of empirical work has been conducted on or around the idea of social amplification, for example showing that the largest influence on amplification is typically organisational misconduct (Freudenberg, 2003). It continues to be an important topic in the risk literature, not least in connection with zoonosis risks (eg, Heberlein and Stedman, 2009; Lewis and Tyshenko, 2009).

There has always been a substantial critique of the basic idea of social risk amplification. Its implication that there is some true or accurate level that becomes amplified is hard to accept in many controversial and contested cases where expertise is lacking or where there is no expert consensus (Rayner, 1988). The phenomenon of ‘dueling experts’ is common in conflicts over environmental health, for instance (Nelkin, 1995). More generally, the concept of risk amplification seems to suggest that there is a risk ‘signal’ that is outside the social system and is somehow amplified by it (Rayner, 1988). This seems misconceived when we take the view that ultimately risk itself is a social construction (Hilgartner, 1992) or overlay on the world (Jasanoff, 1993). And it naturally leads to the view that contributors to the amplification, such as the media (Bakir, 2005), need to be managed more effectively, and that risk managers should concentrate on fixing the mistake in the public mind (Rip, 1988), when often it may be the expert assessment that is mistaken.

It thus becomes hard to sustain the idea that there is a social process by which true levels of risk get distorted. And this appears to undermine the possibility that risk managers can have a way of anticipating very high or very low levels of social anxiety in any particular case. Once risk amplification becomes no more than a subjective judgment by one group on another social group's risk responses, it is hard to see how risk issues can be dealt with on an analytical basis. However, subjective beliefs about risk can produce objective behaviours, and behaviours can interact to produce particular outcomes. And large discrepancies in risk beliefs between different groups are still of considerable interest, whether or not we can know which beliefs are going to turn out to be more correct. In the remainder of this article we therefore explore the consequences of the idea that social risk amplification is nothing more than an attribution, or judgment that one social actor makes of another, and try to see what implications this might have for risk managers based on a systems dynamics model. Before this, however, we describe the fieldwork whose principal findings were meant to provide the main structural properties of the model.

Table 1 Data collection

Method	*Informant(s)*	*Number*
Focus groups	Academic researchers (pilot)	3
	Graduate students in management or social science	5
	Mothers of young children	7
	Retired people	5
	Livestock farmers (1)	8
	Livestock farmers (2)	12
	Veterinarians on PhD programme	5
	Agricultural officials (1)	6
	Agricultural officials (2)	5
	Food safety officials	4
Individual interviews	Virologists and microbiologists	3
	Public health, union and NGO officials	7
	Journalists and broadcasters	3

Fieldwork

Method

The aim of the fieldwork was to explore how social actors reason about the risks of recent zoonotic disease outbreaks, and in particular how they make judgments of other actors systematically amplifying or attenuating such risks. This involved a grounded, qualitative study of what a number of groups said in the course of a number of unstructured interviews and focus groups. It follows the general principle of using qualitative empirical work as a basis for systems dynamics modelling (Luna-Reyes and Andersen, 2003). Focus groups were used where possible, for both lay and professional or expert actors; individual interviews were used where access could only be gained to relevant groups (such as journalists) as individuals. The participants were selected from a range of groups having a stake in zoonotic outbreaks such as avian influenza incidents and are listed in Table 1.

The focus groups followed a topic guide that was initially used in a pilot focus group and continually refined throughout the programme. They started with a short briefing on the specific topic of zoonotic diseases, with recent, well-publicised examples. The professional and expert groups were also asked to explain their roles in relation to the management of zoonotic diseases. Participants were then invited to consider recent cases and other examples they knew of, discuss their reactions to the risks they presented, and discuss the way the risks had been, or were being, managed. Their discussions were recorded and the recordings transcribed except in two cases where it was only feasible to record researcher notes. The individual interviews followed the same format.

Analysis of the transcripts followed a typical process of grounded theorising (Glaser and Strauss, 1967), in which the aim was to find a way of categorising participants' responses that gave some theoretical insight into the principle of risk amplification as a subjective attribution. The categories were arrived at in a process of 'constant comparison' of the data and emerging, tentative categories until all responses have been satisfactorily categorised in relation to each other (Glaser, 2002). In Glaser's words, 'Validity is achieved, after much fitting of words, when the chosen one best represents the pattern. It is as valid as it is grounded'. Our approach also drew on template analysis (King, 1998) in that we started with the basic categories of attributing risk amplification and risk attenuation, not a blank sheet. A fuller account of the analysis process and findings is given in a parallel publication (Busby and Duckett, 2012).

Findings

The first main theme to emerge from the data was the way in which actors privilege their own views, and construct reasons to hold on to them by finding explanations for other views as being systematically exaggerated or underplayed. It is surprising in a sense that this was relatively symmetrical. We expected expert groups to characterise lay groups as exaggerating or underplaying risk, but we also expected lay groups to use authoritative risk statements from expert groups and organisations of various kinds as ways of correcting their own initial and tentative beliefs. But there was no evidence for this kind of corrective process.

The reasons that informants gave for why other actors systematically amplify or attenuate risk were categorised under five main headings: cognition, or the way they formed their beliefs; disposition, or their inherent natures; situation, or the particular circumstances; strategy, or deliberate, instrumental action; and structure, or basic patterns in the social or physical world. For example, one group saw the highly pathogenic avian influenza (HPAI) outbreak at Holton in the UK in 2007 as presenting a serious risk and explained the official advice that it presented only a very small risk as arising from a conspiracy between industry and government that the dispositions of the two naturally created.

This second main theme was that some groups of informants often lacked specific and direct knowledge about relevant risks, and resorted to reasoning about other actors' responses to those risks. This reasoning involved moderating those observations with beliefs about whether other actors are inclined to amplify or attenuate risk. Lay groups received information through the media but they had definite, and somewhat clichéd, beliefs about the accuracy of risk portrayals in the media, for example. Thus some informants saw the media treatment of HPAI outbreaks as risk amplifying and portrayed the media as having an incentive to sensationalise coverage, but others (particularly virologists) saw media coverage as risk attenuating out of scientific ignorance.

A third theme was that risk perceptions often came from the specific associations that arose in particular cases. For example, the Holton HPAI outbreak involved a large food processing firm that had earlier been involved in dietary and nutritional controversies. The firm employed intensive poultry rearing practices and was also importing partial products from a processor abroad. This particular case therefore bound together issues of intensive rearing, global sourcing, zoonotic outbreaks and lifestyle risks—incidental associations that enabled some informants to perceive high levels of risk and indignation, and portray others as attenuating this risk.

The fourth theme was that some actors have specific reasons to overcome what they see as other actors' amplifications or attenuations. They do not just discount another actor's distortions but seek to change them. For example, staff in one government agency believed they had to correct farmers who were underplaying risk and not practicing sufficient bio-security, and also correct consumers who were exaggerating risk and boycotting important agricultural products. Such actors do not simply observe other actors' expressed risk levels but try to communicate in such a way as to influence these expressed levels—for example through awareness-raising campaigns.

The fieldwork therefore pointed to a model in which actors like members of the public based their risk evaluations on what they were told by others, corrected in some way for what they expected to be others' amplifications or attenuations; discrepancies between their current evaluations and those of others would be regarded as evidence of such amplifications, rather than being used to correct their own evaluations. The findings also indicated a model in which risk managers would communicate risk levels in a way that was intended to overcome the misconceptions of actors like the public. These are the underpinning elements of the models we describe below.

Systems dynamics was a natural choice for this modelling on several grounds. First, there is an inherent stress on endogeneity in the basic idea of social risk amplification, and in particular in the notion that it is an attribution. Risk responses first and foremost reflect the way people think about risks and think about the responses of other people to those risks. Second, the explicit and intuitive representation of feedback loops was important to show the reflective nature of social behaviour: how actors see the impact of their risk responses on other actors and modify their responses accordingly. Third, memory plays an important part in this, since the idea that some actor is a risk amplifier will be based on remembering their past responses, and the accumulative capacity of stocks in systems dynamics provides an obvious way of representing social memory. Developing a systems dynamics model on the grounded theory therefore followed naturally, and helped to add a deductive capability to the essentially inductive process of grounded theory (Kopainsky and Luna-Reyes, 2008). Kopainsky and Luna-Reyes (2008) also point out that grounded theory can produce large and rich sets of evidence and overly complex theory, making it important to have a rigorous approach to concentrating on small numbers of variables and relationships. Thus, in the modelling we describe in the next section, the aim was to try to represent risk amplification with as little elaboration as possible, so that it would be clear what the consequences of the basic structural commitments might be. This meant reduction to the simplest possible system of two actors, interacting repeatedly over time during the period of an otherwise static risk event (such as a zoonosis outbreak).

Modelling

Background

Applications of systems dynamics have been wide-ranging, addressing issues in domains ranging from business (Morecroft and van der Heijden, 1992) to military (Minami and Madnick, 2009), from epidemiology (Dangerfield *et al*, 2001) to diffusion models in marketing (Morecroft, 1984), from modelling physical state such as demography (Meadows *et al*, 2004) to mental state such as trust (Luna-Reyes *et al*, 2008; Martinez-Moyano and Samsa, 2008). Applications to issues of risk, particularly risk perception, are much more limited. There has been some application of system dynamics to the diffusion of fear and SARF, specifically (Burns and Slovic, 2007; Sundrani, 2007), but not to the idea of social amplification as an attribution.

Probably the closest examples to our work in the system dynamics literature deal with trust. Luna-Reyes *et al* (2008), for example, applied system dynamics to investigate the role of knowledge sharing in building trust in complex projects. To make modelling tractable, the authors make several simplifying assumptions including the aggregation of various government agencies as a single actor and various service providers as another actor. Each actor accumulates the knowledge of the other actor's work, and the authors explore the dynamics that emerge from their interaction. Greer *et al* (2006) modelled similar interactions—this time between client and contractor—each having its own, accumulated understandings of a common or global quantity (in this case the 'baseline' of work a project). Martinez-Moyano and Samsa (2008) developed a system dynamics model to support a feedback theory of trust and confidence. This represented the mutual interaction between two actors (government and public) in a social system where each actor assesses the trustworthiness of the other actor over time, with both actors maintaining memories of the actions and outcomes of the other actor. Our approach draws from all these studies, modelling a system in which actors interact on the basis of remembered, past interactions as they make assessments of some common object. The actors are in fact groups of individuals who are presumed to be acting in some concerted way. Although this may seem questionable there are several justifications for doing so: (1) the aim is not to represent the diversity of the social world but to explore the consequences of specific ideas about phenomena like social risk amplification; (2) in some circumstances a 'risk manager' such as a private corporation or a government agency may act very much like a unit actor, especially when it is trying to coordinate its communications in the course of risk events; (3) equally in some circumstances it may be quite realistic to see a 'public' as acting in a relatively consensual way whose net, aggregate or average response is of more interest than the variance of response.

In the following sections we develop a model in three stages. In the first, we represent the conventional view of social risk amplification; in the second, we add our subjective, attributional approach in a basic form; and in the third we make the attributional elements more realistically complex. The aim is to explore the implications of the principal findings of the fieldwork, and our basic theoretical commitments to social risk amplification as an attribution, with as little further adornment as possible, while also incorporating elements shown in the literature to be important aspects of risk amplification.

First model: basic elements from the traditional view

In the first model, shown in Figure 1, we represent in a simple way the basic notion of social risk amplification. The fundamental idea is that risk responses are socially developed, not simply the sum of the isolated reactions of unconnected individuals. The model represents a population as being in one of two states of worry. This is simpler than the three-state model of Burns and Slovic (2007) but it is unclear what an intermediate state like being 'concerned' particularly adds to the model. There is also no need for a recovering or removal state, as in SIR (Susceptible Infectious Recovered) models (Sterman, 2004, p 303), since there is no concept of immunity and it seems certain that people can be worried by the same thing all over again.

The flow from an Unworried state to a Worried state is a function of how far the proportion in the Worried state exceeds that normally expected in regard to a risk event such as a zoonotic disease outbreak. Members of the public expect some of their number to become anxious in connection with any risk issue: when, through communication or observation, they realise this number exceeds expectation, this in itself becomes a reason for others to become anxious. This observation of fellow citizens is not medium-specific, so it is a combination of observation by word-of-mouth, social networks and broadcast media. In terms of how this influences perception, various processes are suggested in the literature. For example, there is a variety of 'social contagion' effects (Levy and Nail, 1993; Scherer and Cho, 2003) relevant to such situations. Social learning (Bandura, 1977) or 'learning by proxy' (Gardner *et al*, 2000) may also well be important. We do not model specific mechanisms but only an aggregate process by which the observation of worry influences the flow into a state of being worried.

The flow out of the Worried state is a natural relaxation process. It is hard to stay worried about a specific issue for any length of time, and the atrophy of vigilance is reported in the literature (Freudenberg, 2003). There is also a base flow between the states, reflecting the way in which—in the context of any public risk event—there will be some small proportion of the population that becomes worried, irrespective of peers and public information. This base flow also has the function of dealing with the 'startup problem' in which zero flow is a potential equilibrium for the model (Sterman, 2004, p 322).

The public risk perception in this model stands in relation to an expert, supposedly authoritative assessment of the risk. People worry when seeing others worry, but moderate this response when exposed to exogenous information—the expert or managerial risk assessment. What ultimately regulates worry is some combination of these two elements and it is this regulatory variable that we call a resultant 'risk perception'. Unlike Burns and Slovic (2007) we do not represent this as a stock because it is not anyone's belief, and so need not have inertia. The fact that various members of the public are in different states of worry means that there is no belief that all share, as such. Instead, risk perception is an emergent construct on which flows between unworried and worried states depend (and which also determines how demand for risky goods changes, as we explain below). In the simplest model we simply take this resultant risk perception as a weighted

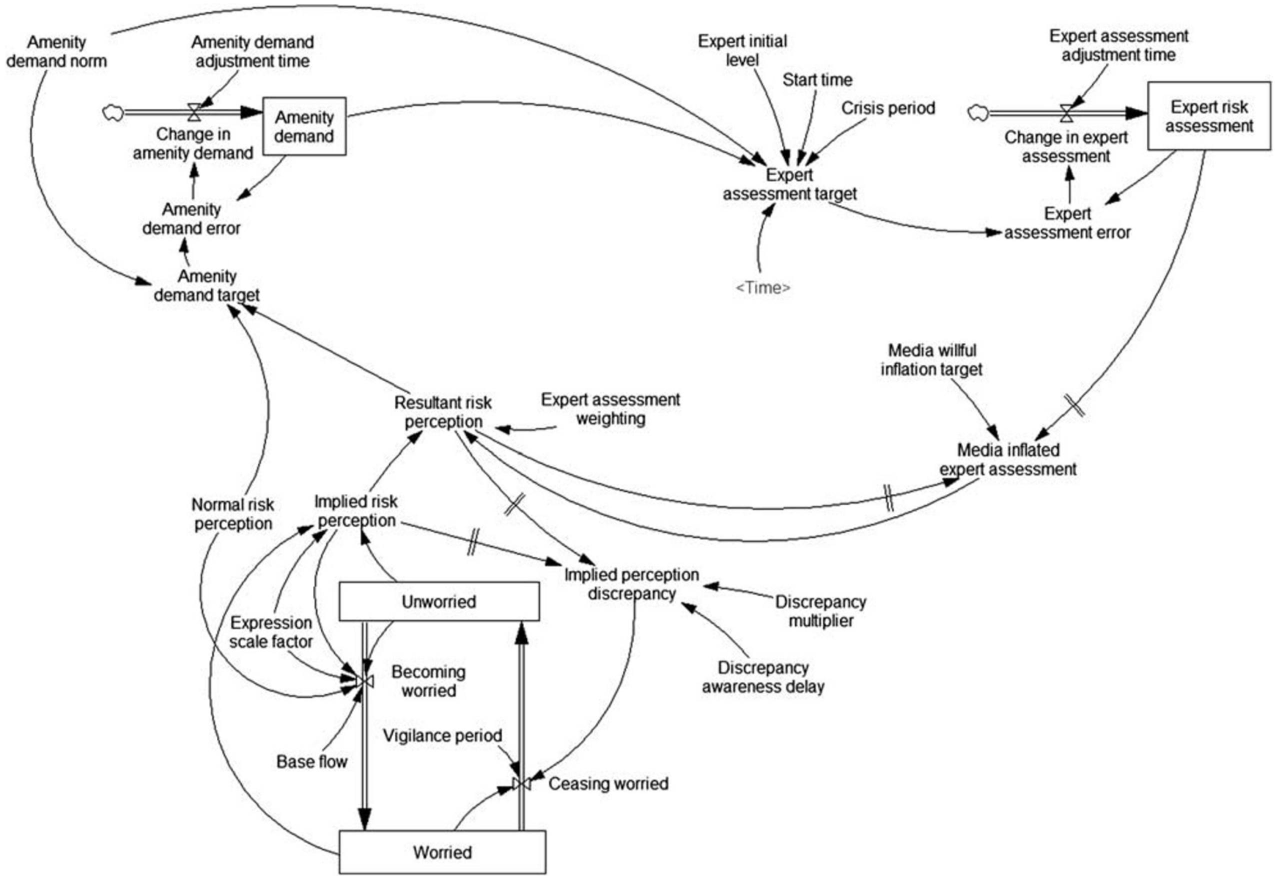

Figure 1 Base model of social amplification of risk.

geometric mean of the risk implied by the proportion of the population worried and the publically known expert risk assessment.

The expert assessment grows from zero toward a finite level, for a certain period, before decaying again to zero. This reflects a time profile for typical risk events—for example zoonotic outbreaks such as SARS—where numbers of reported cases climb progressively and rapidly to a peak before declining (eg, Leung *et al*, 2004). The units for risk perception and the expert assessment are arbitrary, but for exposition are taken as probabilities of individual fatality during a specific risk event. Numerical values of the exogenous risk-related variables are based on an outbreak in which the highest fatality probability is 10^{-3}. But risks in a modern society tend to vary over several orders of magnitude. Typically, individual fatality probabilities of 10^{-6} are regarded as 'a very low level of risk', whereas risks of 10^{-3} are seen as very high and at the limit of tolerability for risks at work (HSE, 2001). Because both assessed and perceived risks are likely to vary widely, discrepancies between risk levels are represented as ratios.

The way in which the expert assessment is communicated to the public is via some homogenous channel we have simply referred to as the 'media'. In our basic model we represent in very crude terms the way in which this media might exaggerate the difference between expert assessment and public perception. But the SARF literature suggests there is no consistent relationship between media coverage and either levels of public concern or frequencies of fatalities (Breakwell and Barnett, 2003; Finkel, 2008), so the extent of this exaggeration is likely to be highly case specific. It is also possible that the media have an effect on responses by exaggerating to a given actor its own responses. The public, for example, could have an inflated idea of how worried they are because newspapers or blogs portray it to be so. But we do not represent this because it is so speculative and may be indeterminable empirically.

Finally, the base model also represents the way in which risk perception influences behaviour, in particular the consumption of the goods or services that expose people to the risk in question. The 2005 Holton UK outbreak of HPAI, for example, occurred at a turkey meat processing plant and affected demand for its products; the SARS outbreak affected demand for travel, particularly aviation services. Brahmbhatt and Dutta (2008) even refer to the economic disruption caused by 'panicky' public responses as 'SARS type' effects. There are many complications here, not least that reducing consumption of one amenity as a result of heightened risk perception may increase consumption of a riskier amenity. Air travel in the US fell after 9/11 but travel by car increased and aggregate risk levels were said to have risen in consequence (Gigerenzer, 2006). A further complication is that in certain situations, such as bank runs (Diamond and Dybvig, 1983), risk perceptions are directly self-fulfilling rather than self-correcting. The most common effect is probably that heightened risk perceptions will lead to reduced demand for the amenity that causes exposure, leading to reductions in exposure and reductions in the expert risk assessment, but it is worth noting that the effect is case-specific. The expert risk assessment is therefore not exogenous, and there is a negative feedback loop that operates to counteract rising risk perceptions.

Second model: adding an attributional subsystem

As we show later from the simulation outcomes, the base model shows a public risk perception that can be considerably larger than the expert risk assessment. It therefore seems to show 'risk amplification'. But there is no variable that stands for risk in the model: there are only beliefs about risk (called either assessments or perceptions). The idea that social risk amplification is a subjective attribution, not an objective phenomenon, means that this divergence of risk perception and expert assessment does not amount to risk amplification. And it says that actors see others as being risk amplifiers, or attenuators, and develop their responses accordingly. This means that we need to add to SARF, and the basic model of the previous section, the processes by which actors observe, diagnose and deal with other actors' risk assessments or perceptions. What our fieldwork revealed was that the social system did not correct 'mistaken' risk perceptions in some simple-minded fashion. In other words, it was not the case that people formed risk perceptions, received information about expert assessment, and then corrected their perceptions in the correct direction. Instead, as we explained earlier, they found reasons why expert assessments, and in fact the risk views of any other group, might be subject to systematic amplification or attenuation. They then corrected for that amplification. Risk managers, on the other hand, had the task of overcoming what they saw as mistaken risk responses in other groups, not simply correcting for them.

Therefore in the second model, shown in Figure 2, we now have a subsystem in which a risk manager (a government agency or an industrial undertaking in the case of zoonotic disease outbreaks) observes the public risk perception in relation to the expert risk assessment, and communicates a risk level that is designed to compensate for any discrepancy between the two. Commercial risk managers will naturally want to counteract risk amplification that leads to revenue losses from product and service boycotts, and governmental risk managers will want to counteract the risk amplification that produces panic and disorder. As Beck *et al* (2005) report, the UK BSE inquiry found that risk managers' approach to communicating risk 'was shaped by a consuming fear of provoking an irrational public scare'. The effect is symmetrical to the extent that the public in turn observes discrepancies between managerial communications and its own risk perceptions, and attributes amplification or attenuation accordingly.

Attributions are based on simple memory of past observations. This historical memory of another actor's apparent distortions is sometimes mentioned in the SARF literature (Kasperson *et al*, 1988; Poumadere and Mays, 2003). This memory is represented as stocks of observed discrepancies, reaching a level $M_i(t)$for actor i at time t. The managerial memory, for example, is

$$M_{\text{manager}}(\tau) = \int_0^{\tau} \lg\left(\frac{R_{\text{public}}(t)}{R_{\text{expert}}(t)}\right) \mathrm{d}t$$

$M_i(t) > 0$ implies that actor i sees the other actor as exaggerating risk, while $M_i(t) < 0$ implies perceived attenuation. The specific deposits in an actor's memory are not retrievable, and equal weight is given to every observation that contributes to it. The perceived scale of amplification is the time average of memory content, and the confidence the actor has in this perceived amplification is $1 - e^{-|M(t)|}$ where confidence grows logarithmically towards unity as the magnitude of the memory increases. The managerial actor modifies the risk level it communicates by the perceived scale of public amplification raised to the power of its confidence, while the public adjusts the communicated risk level it takes account of by the perceived scale of managerial attenuation raised to the power of its confidence in this.

Third model: adding complexity to the model

In the third model, in Figure 3, we add three elements found in the risk amplification literature that become especially relevant to the idea of risk amplification as a subjective attribution: confusion, distrust and differing perceptions about the significance of behavioural change. The confusion issue reflects the way an otherwise authoritative actor's view tends to be discounted if it shows evidence of confusion, uncertainty or inexplicable change. Two articles in the recent literature on zoonosis risk (Bergeron and Sanchez, 2005; Heberlein and Stedman, 2009) specifically describe the risk amplifying effect of the authorities seeming confused or uncertain. The distrust issue reflects the observation that 'distrust acts to heighten risk perception . . . ' (Kasperson *et al*, 2003), and that it is 'associated with perceptions of deliberate distortion of

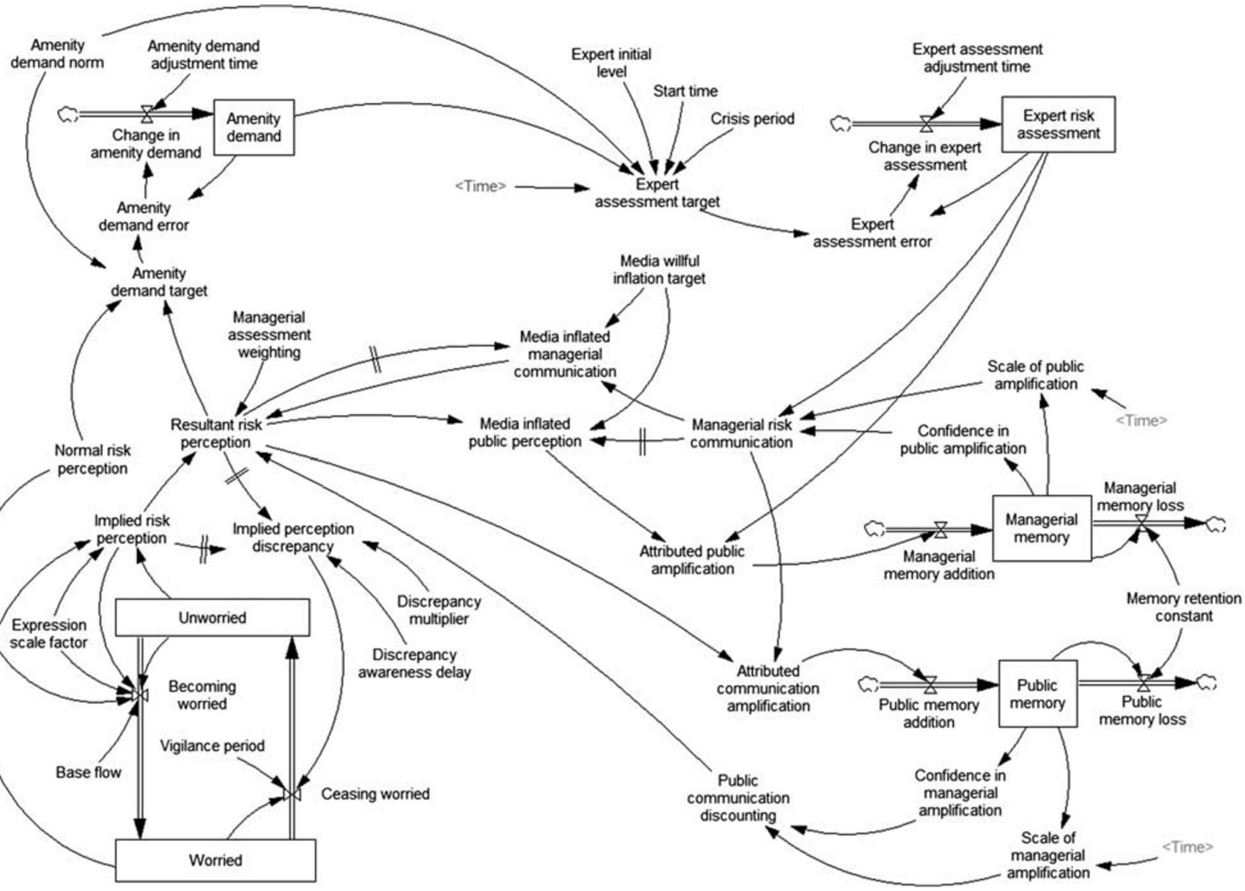

Figure 2 Model of the attributional view of risk amplification.

information, being biased, and having been proven wrong in the past' (Frewer, 2003, p 126). A distinguishing aspect of trust and distrust is the basic asymmetry such that trust is quick to be lost and slow to be gained (Slovic, 1993).

In Figure 3, the confusion function is based on the rate of change of attributed amplification, not rate of change communication itself, since some change in communication might appear justified if correlated with a change in public perception: $G = 1 - e^{-g|C_g(t)|}$, where $C_g\ (t)$ is the change in managerial amplification in unit time. The distrust function is based on the extent of remembered attributed amplification: $F = 1 - e^{-f|M_g(t)|}$, where $M_g(t)$ is the memory of managerial risk amplification at time t and f is the distrust parameter. There is no obvious finding in the literature that would help us set the value of such a parameter. The combination of the confusion and distrust factors is a combination of an integrator and a differentiator. It is used to determine how much weight is given to managerial risk communications in the formation of the resultant risk perception. It is defined such that as distrust and confusion both approach unity, this weight w tends to zero: $w = w_{\max}(1-G)(1-F)$. This weight was exogenous in the previous model, so the effect of introducing confusion and distrust is also to endogenise the way observation of worry is combined with authoritative risk communication.

The third addition in this model is an important disproportionality effect. The previous models assume that risk managers base their view of the public risk perception on some kind of direct observation—for example, through clamour, media activity, surveys and so on. In practice, the managerial view is at least partly based on the public's consumption of the amenity that is risk, for example the consumption of beef during the BSE crisis, or flight bookings and hotel reservations during the SARS outbreak. The problem is that when a foodstuff like beef becomes a risk object it may be easy for many people to stop consuming it, and such a response from the consumer's perspective can be proportionate to even a mild risk assessment. Reducing beef consumption is an easy precaution for most of the population to take (Frewer, 2003), so rational even when there is little empirical evidence that there is a risk at all (Rip, 2006). Yet this easy response of boycotting beef may be disastrous for the beef industry, and therefore seem highly *dis*proportionate to the industry, to related industries and to government agencies supporting the industry.

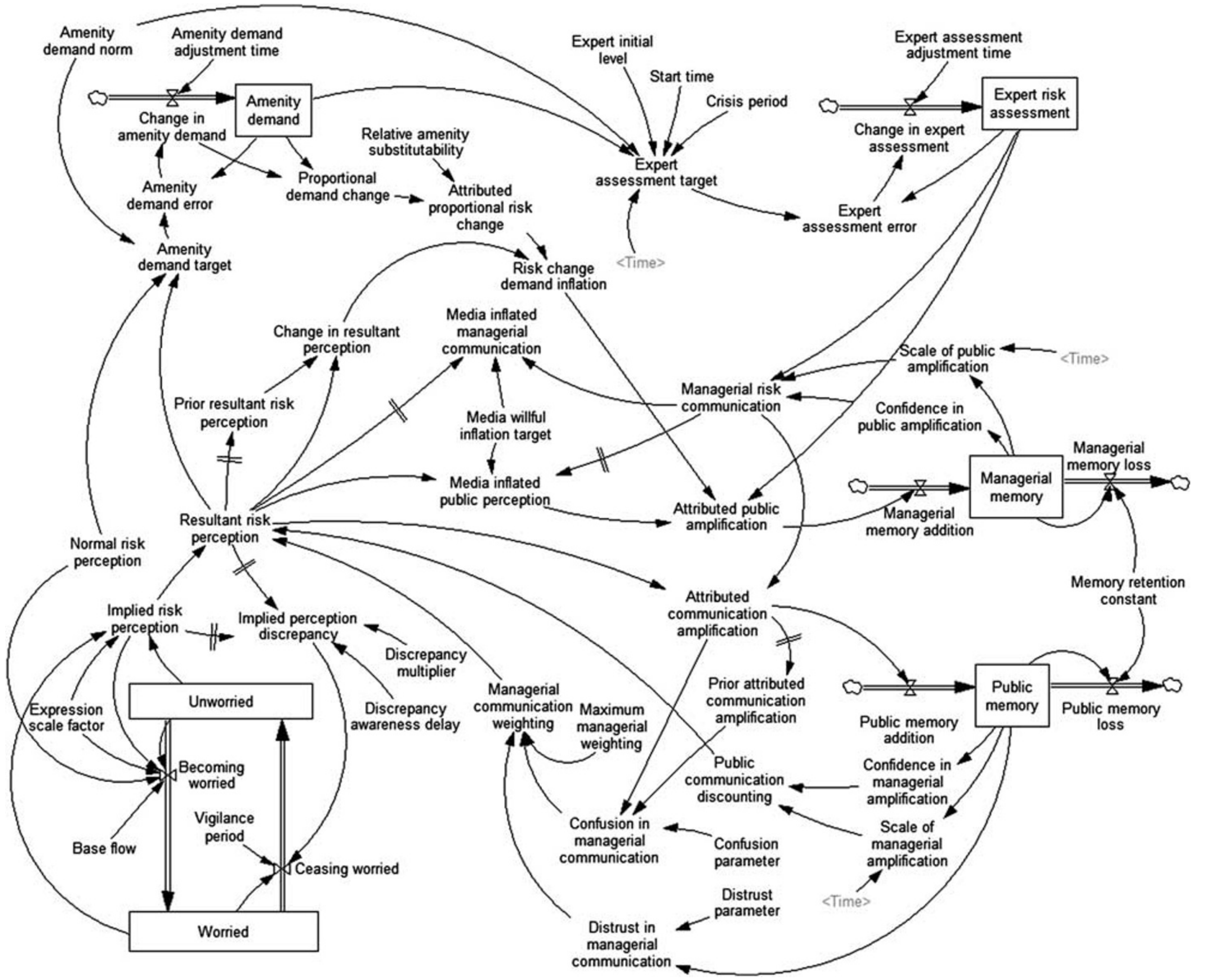

Figure 3 Model of a more complex attributional view of risk amplification.

Unfortunately there is considerable difficulty in quantifying this effect in general terms. Recent work (Mehers, 2011) looking at the effect of heightened risk perceptions around the avian influenza outbreak at a meat processing plant suggests that the influence on the demand for the associated meat products was very mixed. Different regions and different demographic groups showed quite different reactions, for example, and the effect was confounded by actions (particularly price changes) taken by manufacturer and retailers. Our approach is to represent the disproportionality effect with a single exogenous factor—the relative substitutability of the amenity for similar amenities on the supply and demand side. The risk manager interprets any change in public demand for the amenity multiplied by this factor as being the change in public risk perception. If the change in this inferred public risk perception exceeds that observed directly (for example by opinion survey), then it becomes the determinant of how risk managers think the public are viewing the risk in question. This relative substitutability is entirely a function of the specific industry (and so risk manager) in question: there is no 'societal' value for such a parameter, and the effects of a given risk perception on amenity demand will always be case specific. For example, Brahmbhatt and Dutta (2008) reported that the SARS outbreak led to revenue losses in Beijing of 80% in tourist attractions, exhibitions and hotels, but of 10-50% in travel agencies, airlines, railways and so on. The effects are substantial but a long way from being constant.

Behaviour

In this section we briefly present the outcomes of simulation with two aims: first to show how the successive models produce differences in behaviour, if at all, and thereby to assess how much value there is in the models for policymakers; second to assess how much uncertainty in outcomes such as public risk perception is produced by uncertainty in the exogenous parameters.

Model behaviour

Figure 4 shows the behaviour of the three successive models in terms of public risk perception and expert risk assessment. For the three models, the exogenous variables are set at their modal values and when variables are shared between models they have the same values. The expert risk assessment is thus very similar for each model, as shown in the figure, rising towards its target level, falling as public risk perception reduces exposure, and then ceasing as the crisis ends around Day 40. In the base model, the public risk perception is eight times higher than the expert assessment at its peak, which occurs some 20 days after that in the expert assessment. But once the attributional view of risk amplification is modelled, this disparity becomes much greater, and it occurs earlier. In the simple attributional system the peak discrepancy is over 40 times, and in the complex attributional system nearly 400 times, both occurring within 8 days of the expert assessment peak. Thus the effect of seeing risk amplification as the subjective judgment of one actor about another is, given the assumptions in our models, to polarise risk beliefs much more strongly and somewhat more rapidly. We can no longer call the outcome a ‘risk amplification’ since, by assumption, there is no longer an objective risk level exogenous to the social system. But there is evidently strong polarisation.

There is some qualitative difference in the time profile of risk perception between the three models, as shown in the previous figure where the peak risk perception occurs earlier in the later models. There are also important qualitative differences in the time profiles of stock variables amenity demand and worried population, as shown in Figure 5. When the attributional view is taken, both demand and worry take longer to recover to initial levels, and when the more complex attributional elements are modelled (the effects of mistrust, confusion and different perceptions of the meaning of changes in demand), the model indicates that little recovery takes place at all. The scale of the recovery depends on the value of the exogenous parameters, and some of these (as we discuss below) are case specific. But of primary importance is the way the weighting given to managerial communications or expert assessment is dragged down by public attributions. This result indicates the importance of a complex, attributional view of risk amplification. Unlike the base model, in the attributional model it is much more likely there will be an indefinite residue from a crisis—even when the expert assessment of risk falls to near zero.

Figures 6 and 7 show the time development of risk perception in the third model in terms of the mean outcome with (a) 95% confidence intervals on the mean and (b) tolerance intervals for 95% confidence in 90% coverage over 1000 runs, with triangular distributions assigned to the exogenous parameters and plausible ranges based solely on the author’s subjective estimates. The exogenous parameters fall into two main groups. The first group is of case-specific factors and would be expected to vary between risk events. This includes, for example, the relative substitutability of the amenity that is the carrier of the risk, and the latency before changes in demand for this amenity change the level of risk exposure. The remaining parameters are better seen as social constants, since there is no theoretical reason to think that they will vary from one risk event to another. These include factors like the natural vigilance period among the population, the normal flow of people into a state of worry, the latency before people become aware of a discrepancy between emergent risk perception and the proportion of the population that is in a state of worry. Figure 6 shows the confidence and tolerance intervals with the social constants varying within their plausible ranges and the case-specific factors fixed at their modal values, and Figure 7 vice versa. Thus Figure 6 shows the effect of our uncertainty about the character of society,

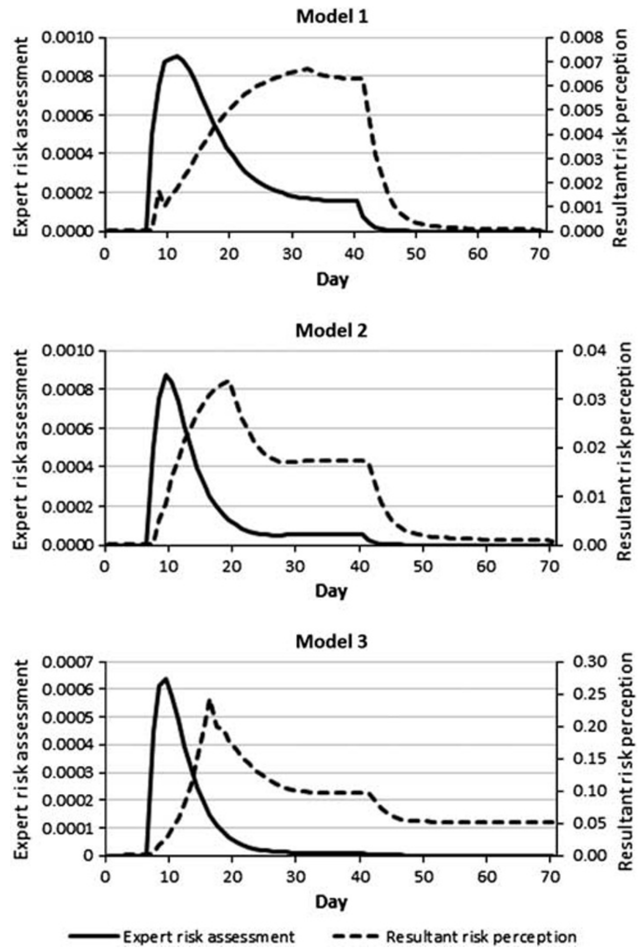

Figure 4 Outcomes of the three models.

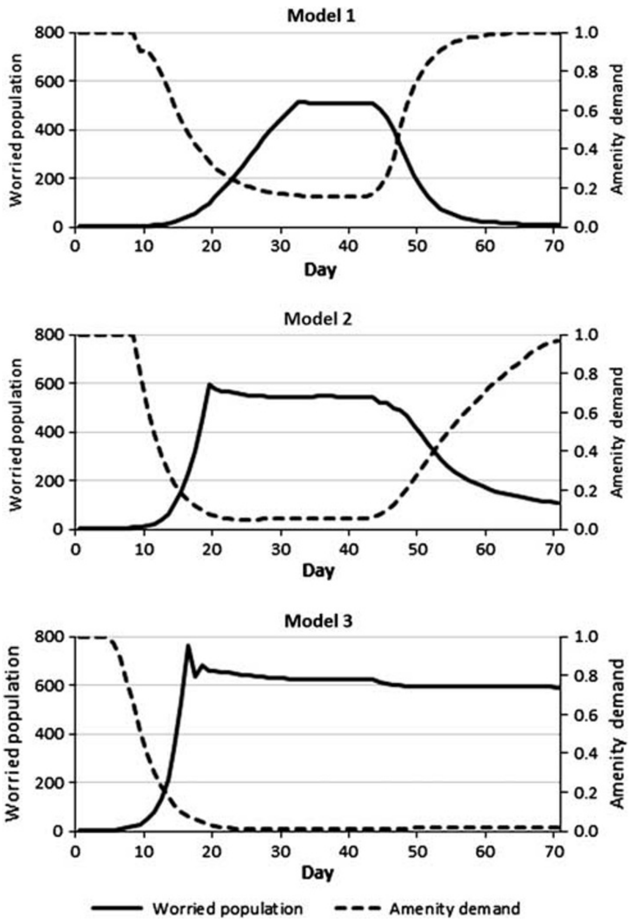

Figure 5 Further outcomes of the three models.

whereas Figure 7 shows the effect of the variability we would expect among risk events. The substantial difference between the means in risk perception between the two figures reflects large differences between means and modes in the distributions attributed to the parameters, which arises because plausible ranges sometimes cover multiple orders of magnitude (eg, the confusion and distrust constants both range from 1 to 100 with modes of 10, and the memory constant from 10 to 1000 with a mode of 100). These figures do not give a complete understanding, not least because interactions between the two sets of parameters are possible, but they show a reasonably robust qualitative profile.

Figure 8 shows the 'simple' correlation coefficients between resultant risk perception and the policy-relevant exogenous parameters over time, as recommended by Ford and Flynn (2005) as an indication of the relative importance of model inputs. At each day of the simulation, the sample correlation coefficient is calculated for each parameter over the 1000 runs. No attempt has been made to inspect whether the most important inputs are correlated, and to refine the model in the light of this. Nonetheless the figure gives some indication of how influential are the most

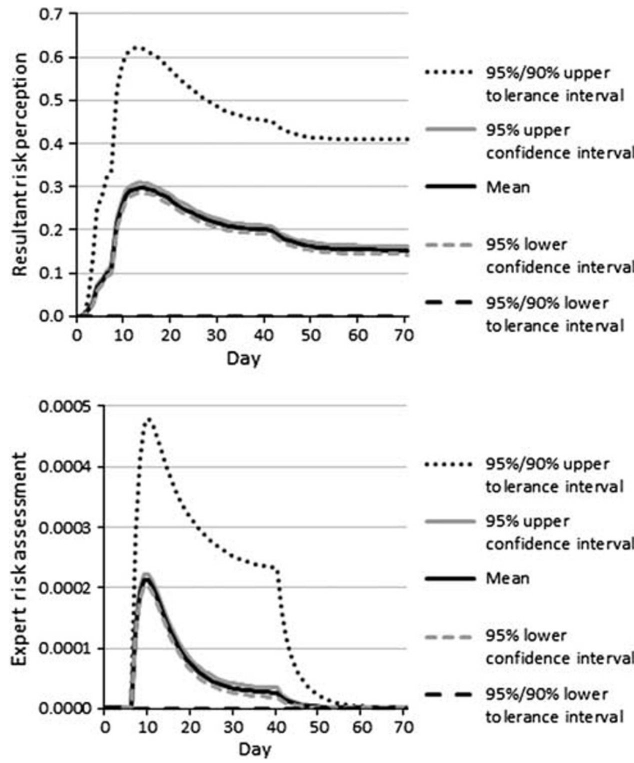

Figure 6 Confidence intervals on the time development of risk perception in the third model, case-specific factors fixed.

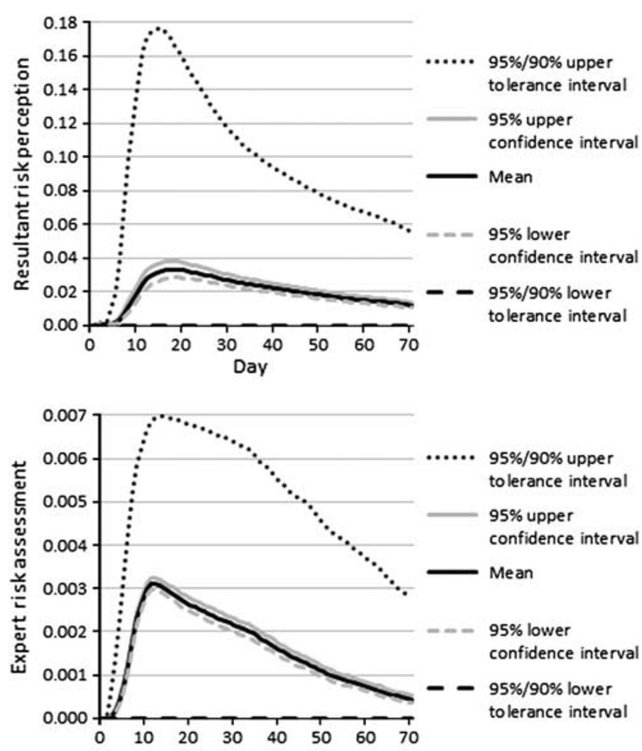

Figure 7 Confidence intervals on the time development of risk perception in the third model, social constants fixed.

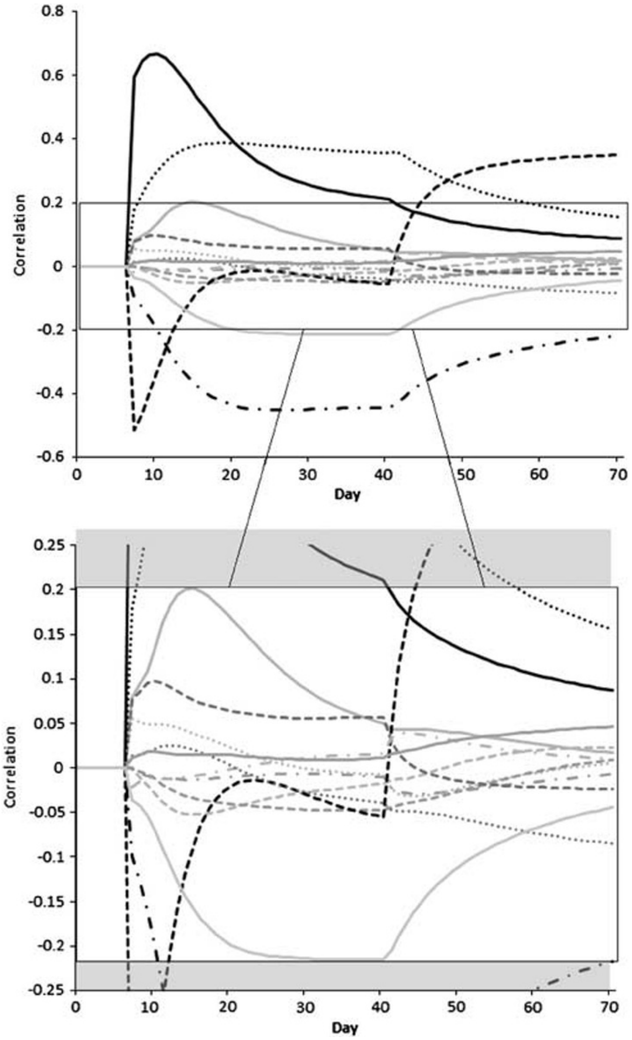

Figure 8 Correlations between exogenous parameters and resultant risk perception over time.

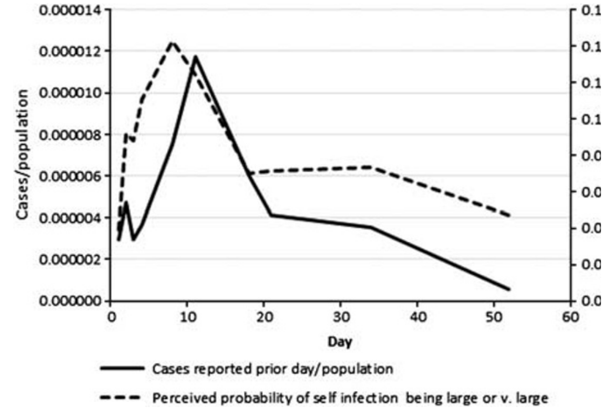

Figure 9 Values from Lau *et al* (2003) survey of perceived infection risk.

prominent parameters: the expert initial assessment level (ie, the original scale of the risk according to expert assessment), the expert assessment adjustment time (ie, the delay in the official estimate reflecting the latest information), the base flow (the flow of people between states of non-worry and worry in relation to a risk irrespective of the specific social influences being modelled) and the normal risk perception (the baseline against which the resultant risk perception is gauged, reflecting a level of risk that would be unsurprising and lead to no increase in the numbers of the worried). The first of these is case-specific, but the other three would evidently be worth empirical investigation given their influence in the model.

Empirical comparisons

It is extremely difficult to test such outcomes against empirical data because cases differ so widely and it is unusual to find data on simultaneous expert assessments and public perceptions over short-run risk events like disease outbreaks, particularly outbreaks of zoonotic disease. But a World Bank paper of 2008, on the economic effects of infectious disease outbreaks (primarily SARS, a zoonotic disease), collected together data gathered on the 2003 SARS outbreak, and some—primarily that of Lau *et al* (2003)—showed the day-by-day development of risk perception alongside reported cases. Figure 9 is based on Lau *et al*'s data (2003), and shows the number of reported cases of SARS as a proportion of the Hong Kong population at the time, together with the percentage of people in a survey expressing a perception that they had a large or very large chance of infection from SARS. The two lines can be regarded as reasonably good proxies for the risk perception and expert assessment outcomes in Figure 4 and they show a rough correspondence: a growth in both perception and expertly assessed or measured 'reality', followed by a decay, in which the perception appears strongly exaggerated from the standpoint of the expert assessment. The perceptual gap is about four orders of magnitude—greater than even the more complex attributional system in our modelling. Moreover, the risk perception peak occurs early, and in fact leads the reported cases peak. It is our models 2 and especially 3 in which the perception peak occurs early (although it never leads the expert assessment peak).

Discussion

The implications of the work

The social amplification of risk framework has always been presented as an 'integrative framework' (Kasperson *et al*, 1988), rather than a specific theory, so there has always been a need for more specific modelling to make its basic concepts precise enough to be properly explored. At the same time, as suggested earlier, its implication that there is some true level of risk that becomes distorted in social responses has been criticised for a long time. We therefore set out to explore whether it is possible to retain some concept of social risk amplification in cases where even expert opinion tends to be divided, the science is often very incomplete, and past expert assessment has been discredited. Zoonotic disease outbreaks provide a context in which such conditions appear to hold.

Our fieldwork broadly pointed to a social system in which social actors of all kinds privilege their own risk views, in which they nonetheless have to rely on other actor's responses in the absence of direct knowledge or experience of the risks in question, in which they attribute risk amplification or attenuation to other actors, and in which they have reasons to correct for or overcome this amplification. To explore how we can model such processes has been the main purpose of the work we have described. And the resulting model provides specific indications of what policymakers need to deal with—a much greater polarisation of risk beliefs, and potentially a residue of worry and loss of demand after the end of a risk crisis. It also has the important implication that risk managers' perspectives should shift, from correcting a public's mistakes about risk to thinking about how their own responses and communications contribute to the public's views about a risk. Our approach helps to endogenise the risk perception problem, recognising that it is not simply a flaw in the world 'out there'. It is thus an important step in becoming a more sophisticated risk manager or manager of risk issues (Leiss, 2001).

It is instructive to compare this model with models like that of Luna-Reyes *et al* (2008) which essentially involve a convergent process arise from knowledge sharing, and the subsequent development of trust. We demonstrate a process in which there is knowledge sharing, but a sharing that is undermined by expectations of social risk amplification. Observing discrepancies in risk beliefs leads not to correction and consensus but to self-confirmation and polarisation. Our findings in some respects are similar to Greer *et al* (2006), who were concerned with discrepancies in the perceptions of workload in the eyes of two actors involved in a common project. Such discrepancies arose not from exogenous causes but from unclear communication and delay inherent in the social system. All this reinforces the long-held view in the risk community, and of risk communication researchers in particular, that authentic risk communication should involve sustained relationships, and the open recognition of uncertainties and difficulties that would normally be regarded as threats to credibility (Otway and Wynne, 1989). The reason is not just the moral requirement to avoid the perpetuation of powerful actors' views, and not just the efficiency requirement to maximise the knowledge base that contributes to managing a risk issue. The reason is also that the structure of interactions can be unstable, producing a polarisation of view that none of the actors intended. Actors engaged with each other can realise this and overcome it.

Limitations of the modelling

A basic limitation to the use of the models to support specific risk management decisions, rather than give more general insight into social phenomena, is that there are very few sources of plausible data for some important variables in the model, such as the relaxation delay defining how long people tend to stay worried about a specific risk event before fatigue, boredom or replacement by worry about a new crisis leads them to stop worrying. It is particularly difficult to see where values of the case-specific parameters are going to come from. Other SD work on risk amplification at least partly avoids the calibration problem by using unit-less normalised scales and subjective judgments (Burns and Slovic, 2007). And one of the benefits of this exploratory modelling is to suggest that such variables are worthwhile subjects for empirical research. But at present the modelling does not support prediction and does not help determine best courses of action at particular points in particular crises.

In terms of its more structural limitations, the model is a small one that concentrates specifically on the risk amplification phenomenon to the exclusion of the many other processes that, in any real situation, risk amplification is connected with. As such, it barely forms a 'microworld' (Morecroft, 1988). It contrasts with related work such as that of Martinez-Moyano and Samsa's (2008) modelling of trust in government, which similarly analyses a continuing interaction between two aggregate actors but draws extensively on cognitive science. However, incorporating a lot more empirical science does not avoid having to make many assumptions and selections that potentially stand in the way of seeing through to how a system produces its outcomes. The more elaborate the model the more there is to dispute and undermine the starkness of an interesting phenomenon. We have had to make few assumptions about the world, about psychology and about sociology before concluding that social risk amplification as little more than a subjective attribution has a strongly destabilising potential. This parsimony reflects Towill's (1993) notion that we start the modelling process by looking for the boundary that 'encompasses the smallest number of components within which the dynamic behaviour under study is generated'. The model attempts to introduce nothing that is unnecessary to working out the consequences of risk amplification as an attribution. As Ghaffarzadegan *et al* (2011) point out in their paper on small models applied to problems of public policy, and echoing Forrester's (2007) argument for 'powerful small models', the point is to gain accessibility and insight. Having only 'a few significant stocks and at most seven or eight major feedback loops', small models can convey the counterintuitive endogenous complexity of situations in a way that policymakers can still follow. They are small enough to show systems in aggregate, to stress the endogeneity of influences on the system's behaviour, and to clearly illustrate how policy resistance comes about (Ghaffarzadegan *et al*, 2011). As a result they are more promising as tools for developing correct intuitions, and for helping actors who may be trapped in a systemic interaction to overcome this and reach a certain degree of self-awareness (Lane, 1999).

Conclusion

The intended contribution of this study has been to show how to model a long-established, qualitative framework for reasoning about risk perception and risk communication, and in the process deal with one of the main criticisms of this framework. The idea that in a society the perception of a risk becomes exaggerated to the point where it bears no relation to our best expert assessments of the risk is an attractive one for policymakers having to deal with what seem to be grossly inflated or grossly under-played public reactions to major events. But this idea has always been vulnerable to the criticism that we cannot know objectively if a risk is being exaggerated, and that expert assessments are as much a product of social processes as lay opinion. The question we posed at the start of the paper was whether, in dropping a commitment to the idea of an objective risk amplification, there is anything left to model and anything left to say to policymakers. Our work suggests that there is, and that modelling risk amplification as something that one social actor thinks another is doing is a useful thing to do. There were some simple policy implications emerging from this modelling. For example, once you accept that there is no objective standard to indicate when risk amplification is occurring, actors are likely to correct for other actors' apparent risk amplifications and attenuation, instead of simple-mindedly correcting their own risk beliefs. This can have a strongly polarising effect on risk beliefs, and can produce residual worry and loss of demand for associated products and services after a crisis has passed. The limitations of the work point to further developments in several directions. First, there is a need to explore various aspects of how risk managers experience risk amplification. For example, the modelling, as it stands, concentrates on the interactions of actors in the context of a single event or issue—such as a specific zoonotic outbreak. In reality, actors generally have a long history of interaction around earlier events. We take account of history *within* an event, but not between events. A future step should therefore be to expand the timescale, moving from intra-event interaction to inter-event interaction. The superposition of a longer term process is likely to produce a model in which processes acting over different timescales interact and cannot simply be treated additively (Forrester, 1987). It also introduces the strong possibility of discontinuities, particularly when modelling organisational or institutional actors like governments whose doctrines can change radically following elections—rather like the discontinuities that have to be modelled to represent personnel changes and consequences like scapegoating (Howick and Eden, 2004).

Another important direction of work would be a modelling of politics and power. It is a common observation in risk controversies that risk is a highly political construction—being used by different groups to gain resources and influence. As Powell and Coyle (2005) point out, the systems dynamics literature makes little reference to power, raising questions about the appropriateness of our modelling approach to a risk amplification subject—both in its lack of power as an object for modelling, and its inattention to issues of power surrounding the use of the model and its apparent implications. Powell and Coyle's (2005) politicised influence diagrams might provide a useful medium for representing issues of power, both within the model of risk amplification and in the understanding of the system in which the model might be influential. The notion, as currently expressed in our modelling, that it is always in one actor's interest to somehow correct another's amplification simply looks naïve.

Acknowledgements—Many thanks are due to the participants in the fieldwork that underpinned the modelling, and to Dominic Duckett who carried out the fieldwork. We would also like to thank the anonymous reviewers of an earlier draft of this article for insights and suggestions that have considerably strengthened it. The work was partly funded by a grant from the UK EPSRC.

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Received March 2010;
accepted May 2012 after two revisions