PERSPECTIVE

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Globally networked risks and how to respond

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Today's strongly connected, global networks have produced highly interdependent systems that we do not understand and cannot control well. These systems are vulnerable to failure at all scales, posing serious threats to society, even when external shocks are absent. As the complexity and interaction strengths in our networked world increase, man-made systems can become unstable, creating uncontrollable situations even when decision-makers are well-skilled, have all data and technology at their disposal, and do their best. To make these systems manageable, a fundamental redesign is needed. A 'Global Systems Science' might create the required knowledge and paradigm shift in thinking.

Globalization and technological revolutions are changing our planet. Today we have a worldwide exchange of people, goods, money, information, and ideas, which has produced many new opportunities, services and benefits for humanity. At the same time, however, the underlying networks have created pathways along which dangerous and damaging events can spread rapidly and globally. This has increased systemic risks[1] (see Box 1). The related societal costs are huge.

When analysing today's environmental, health and financial systems or our supply chains and information and communication systems, one finds that these systems have become vulnerable on a planetary scale. They are challenged by the disruptive influences of global warming, disease outbreaks, food (distribution) shortages, financial crashes, heavy solar storms, organized (cyber-)crime, or cyberwar. Our world is already facing some of the consequences: global problems such as fiscal and economic crises, global migration, and an explosive mix of incompatible interests and cultures, coming along with social unrests, international and civil wars, and global terrorism.

In this Perspective, I argue that systemic failures and extreme events are consequences of the highly interconnected systems and networked risks humans have created. When networks are interdependent[2,3], this makes them even more vulnerable to abrupt failures[4–6]. Such interdependencies in our "hyper-connected world"[1] establish "hyper-risks" (see Fig. 1). For example, today's quick spreading of emergent epidemics is largely a result of global air traffic, and may have serious impacts on our global health, social and economic systems[6–9]. I also argue that initially beneficial trends such as globalization, increasing network densities, sparse use of resources, higher complexity, and an acceleration of institutional decision processes may ultimately push our anthropogenic (man-made or human-influenced) systems[10] towards systemic instability—a state in which things will inevitably get out of control sooner or later.

Many disasters in anthropogenic systems should not be seen as 'bad luck', but as the results of inappropriate interactions and institutional settings. Even worse, they are often the consequences of a wrong understanding due to the counter-intuitive nature of the underlying system behaviour. Hence, conventional thinking can cause fateful decisions and the repetition of previous mistakes. This calls for a paradigm shift in thinking: systemic instabilities can be understood by a change in perspective from a component-oriented to an interaction- and network-oriented view. This also implies a fundamental change in the design and management of complex dynamical systems.

The FuturICT community[11] (see http://www.futurict.eu), which involves thousands of scientists worldwide, is now engaged in establishing a 'Global Systems Science', in order to understand better our information society with its close co-evolution of information and communication technology (ICT) and society. This effort is allied with the "Earth system science"[10] that now provides the prevailing approach to studying the physics, chemistry and biology of our planet. Global Systems Science wants to make the theory of complex systems applicable to the solution of global-scale problems. It will take a massively data-driven approach that builds on a serious collaboration between the natural, engineering, and social sciences, aiming at a grand integration of knowledge. This approach to real-life techno-socio-economic-environmental systems[8] is expected to enable new response strategies to a number of twenty-first century challenges.

BOX 1

Risk, systemic risk and hyper-risk

According to the standard ISO 31000 (2009; http://www.iso.org/iso/catalogue_detail?csnumber=43170), risk is defined as "effect of uncertainty on objectives". It is often quantified as the probability of occurrence of an (adverse) event, times its (negative) impact (damage), but it should be kept in mind that risks might also create positive impacts, such as opportunities for some stakeholders.

Compared to this, systemic risk is the risk of having not just statistically independent failures, but interdependent, so-called 'cascading' failures in a network of N interconnected system components. That is, systemic risks result from connections between risks ('networked risks'). In such cases, a localized initial failure ('perturbation') could have disastrous effects and cause, in principle, unbounded damage as N goes to infinity. For example, a large-scale power blackout can hit millions of people. In economics, a systemic risk could mean the possible collapse of a market or of the whole financial system. The potential damage here is largely determined by the size N of the networked system.

Even higher risks are implied by networks of networks[4,5], that is, by the coupling of different kinds of systems. In fact, new vulnerabilities result from the increasing interdependencies between our energy, food and water systems, global supply chains, communication and financial systems, ecosystems and climate[10]. The World Economic Forum has described this situation as a hyper-connected world[1], and we therefore refer to the associated risks as 'hyper-risks'.

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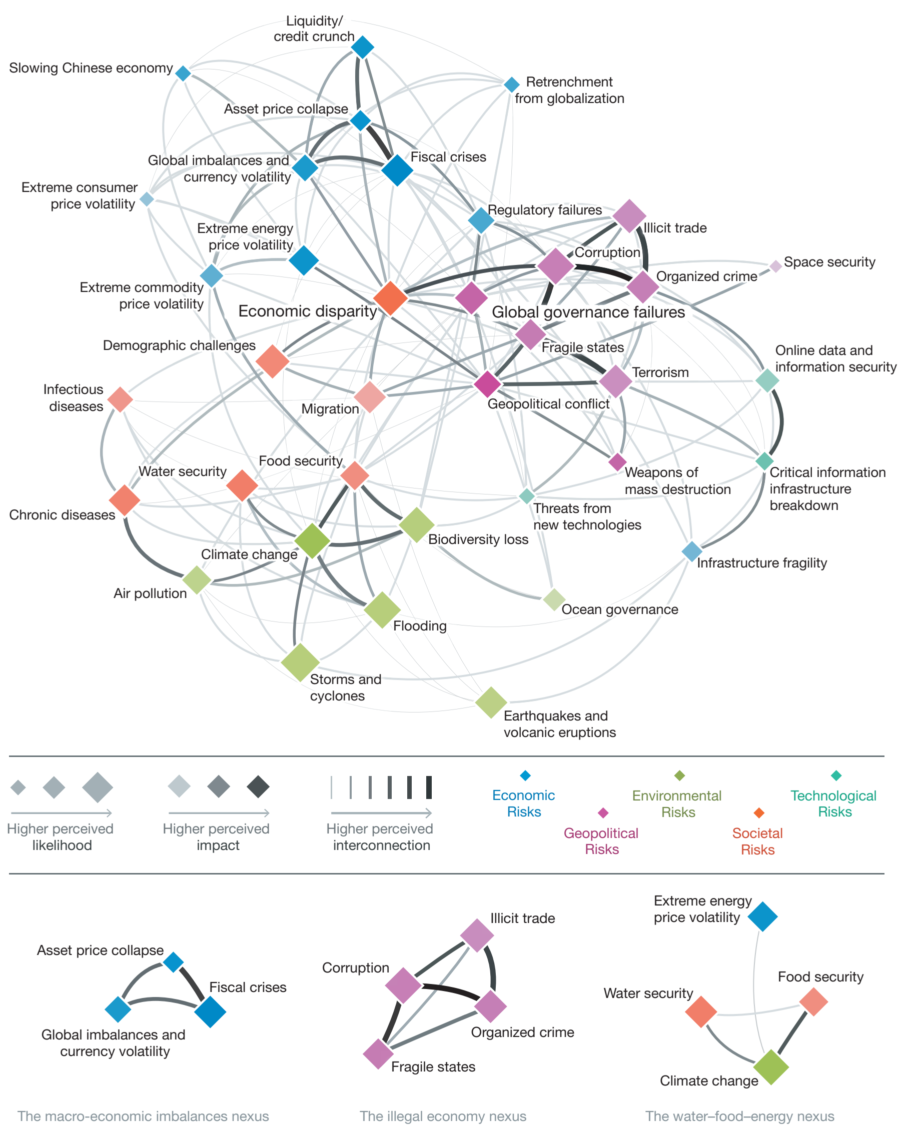


Figure 1 | Risks Interconnection Map 2011 illustrating systemic interdependencies in the hyper-connected world we are living in. Reprinted from ref. 82 with permission of the WEF.

What we know

Overview

Catastrophe theory[12] suggests that disasters may result from discontinuous transitions in response to gradual changes in parameters. Such systemic shifts are expected to occur at certain 'tipping points' (that is, critical parameter values) and lead to different system properties. The theory of critical phenomena[13] has shown that, at such tipping points, power-law (or other heavily skewed) distributions of event sizes are typical. They relate to cascade effects[4,5,14–20], which may have any size. Hence, "extreme events"[21] can be a result of the inherent system dynamics rather than of unexpected external events. The theory of self-organized criticality[22] furthermore shows that certain systems (such as piles of grains prone to avalanches) may be automatically driven towards a critical tipping point. Other work has studied the error and attack tolerance of networks[23] and cascade effects in networks[4,5,14–20,24], where local failures of nodes or links may trigger overloads and consequential failures of other nodes or links. Moreover, abrupt systemic failures may result from interdependencies between networks[4–6] or other mechanisms[25,26].

Surprising behaviour due to complexity

Current anthropogenic systems show an increase of structural, dynamic, functional and algorithmic complexity. This poses challenges for their design, operation, reliability and efficiency. Here I will focus on complex dynamical systems—those that cannot be understood by the sum of their components' properties, in contrast to loosely coupled systems. The following typical features result from the nonlinear interactions in complex systems[27,28]. (1) Rather than having one equilibrium solution, the system might show numerous different behaviours, depending on the respective initial conditions. (2) Complex dynamical systems may seem uncontrollable. In particular, opportunities for external or top-down control are very limited[29]. (3) Self-organization and strong correlations dominate the system behaviour. (4) The (emergent) properties of complex dynamical systems are often surprising and counter-intuitive[30].

Furthermore, the combination of nonlinear interactions, network effects, delayed response and randomness may cause a sensitivity to small changes, unique path dependencies, and strong correlations, all of which are hard to understand, prepare for and manage. Each of these factors is already difficult to imagine, but this applies even more to their combination.

For example, fundamental changes in the system outcome—such as non-cooperative behaviour rather than cooperation among agents—can result from seemingly small changes in the nature of the components or their mode of interaction (see Fig. 2). Such small changes may be interactions that take place on particular networks rather than on regular or random networks, interactions or components that are spatially varying rather than homogeneous, or which are subject to random 'noise' rather than behaving deterministically[31,32].

Cascade effects due to strong interactions

Our society is entering a new era—the era of a global information society, characterized by increasing interdependency, interconnectivity and complexity, and a life in which the real and digital world can no longer be separated (see Box 2). However, as interactions between components become 'strong', the behaviour of system components may seriously alter or impair the functionality or operation of other components. Typical properties of strongly coupled systems in the above-defined sense are: (1) Dynamical changes tend to be fast, potentially outstripping the rate at which one can learn about the characteristic system behaviour, or at which humans can react. (2) One event can trigger further events, thereby creating amplification and cascade effects[4,5,14–20], which implies a large vulnerability to perturbations, variations or random failures. Cascade effects come along with highly correlated transitions of many system components or variables from a stable to an unstable state, thereby driving the system out of equilibrium. (3) Extreme events tend to occur more often than expected for normally distributed event sizes[17,21].

Probabilistic cascade effects in real-life systems are often hard to identify, understand and map. Rather than deterministic one-to-one relationships between 'causes' and 'effects', there are many possible paths of events (see Fig. 3), and effects may occur with obfuscating delays.

Systemic instabilities challenge our intuition

Why are attempts to control strongly coupled, complex systems so often unsuccessful? Systemic failures may occur even if everybody involved is highly skilled, highly motivated and behaving properly. I shall illustrate this with two examples.

Crowd disasters

Crowd disasters constitute an eye-opening example of the eventual failure of control in a complex system. Even if nobody wants to harm anybody else, people may be fatally injured. A detailed analysis reveals amplifying feedback effects that cause a systemic instability[33,34]. The interaction strength increases with the crowd density, as people come closer together. When the density becomes too high, inadvertent contact forces are transferred from one body to another and add up. The resulting forces vary significantly in direction and size, pushing people around, and creating a phenomenon called 'crowd quake'. Turbulent waves cause people to stumble, and others fall over them in an often fatal domino effect. If people do not manage to get back on their feet quickly enough, they are likely to suffocate. In many cases, the instability is created not by foolish or malicious individual actions, but by the unavoidable amplification of small fluctuations above a critical density threshold. Consequently, crowd disasters cannot simply be evaded by policing, aimed at imposing 'better behaviour'. Some kinds of crowd control might even worsen the situation[34].

Financial meltdown

Almost a decade ago, the investor Warren Buffett warned that massive trade in financial derivatives would create mega-catastrophic risks for the economy. In the same context, he spoke of an investment "time bomb" and of financial derivatives as "weapons of mass destruction" (see http://news.bbc.co.uk/2/hi/2817995.stm, accessed 1 June 2012). Five years later, the financial bubble imploded and destroyed trillions of stock value. During this time, the overall volume of credit default swaps and other financial derivatives had grown to several times the world gross domestic product.

But what exactly caused the collapse? In response to the question by the Queen of England of why nobody had foreseen the financial crisis, the British Academy concluded: "Everyone seemed to be doing their own job properly on its own merit. And according to standard measures of success, they were often doing it well. The failure was to see how collectively this added up to a series of interconnected imbalances... Individual risks may rightly have been viewed as small, but the risk to the system as a whole was vast." (See http://www.britac.ac.uk/templates/asset-relay.cfm?frmAssetFileID=8285, accessed 1 June 2012.) For example, while risk diversification in a banking system is aimed at minimizing risks, it can create systemic risks when the network density becomes too high[20].

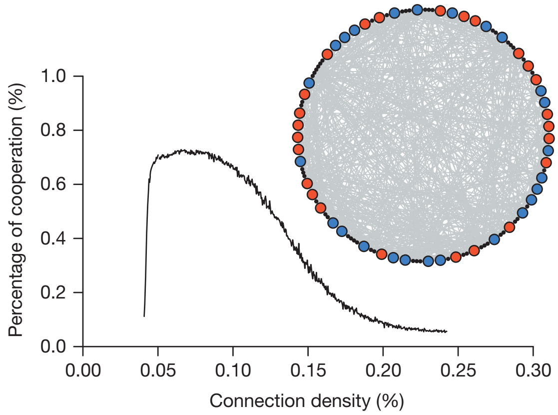


Figure 2 | Spreading and erosion of cooperation in a prisoner's dilemma game. The computer simulations assume the payoff parameters $T = 7$, $R = 6$, $P = 2$, and $S = 1$ and include success-driven migration[32]. Although cooperation would be profitable to everyone, non-cooperators can achieve a higher payoff than cooperators, which may destabilize cooperation. The graph shows the fraction of cooperative agents, averaged over 100 simulations, as a function of the connection density (actual number of network links divided by the maximum number of links when all nodes are connected to all others). Initially, an increasing link density enhances cooperation, but as it passes a certain threshold, cooperation erodes. (See http://vimeo.com/53876434 for a related movie.) The computer simulations are based on a circular network with 100 nodes, each connected with the four nearest neighbours. n links are added randomly. 50 nodes are occupied by agents. The inset shows a 'snapshot' of the system: blue circles represent cooperation, red circles non-cooperative behaviour, and black dots empty sites. Initially, all agents are non-cooperative. Their network locations and behaviours (cooperation or defection) are updated in a random sequential way in 4 steps: (1) The agent plays two-person prisoner's dilemma games with its direct neighbours in the network. (2) After the interaction, the agent moves with probability 0.5 up to 4 steps along existing links to the empty node that gives the highest payoff in a fictitious play step, assuming that noone changes the behaviour. (3) The agent imitates the behaviour of the neighbour who got the highest payoff in step 1 (if higher than the agent's own payoff). (4) The behaviour is spontaneously changed with a mutation rate of 0.1.

Drivers of systemic instabilities

Table 1 lists common drivers of systemic instabilities[32], and what makes the corresponding system behaviours difficult to understand. Current global trends promote several of these drivers. Although they often have desirable effects in the beginning, they may destabilize anthropogenic systems over time. Such drivers are, for example: (1) increasing system sizes, (2) reduced redundancies due to attempts to save resources (implying a loss of safety margins), (3) denser networks (creating increasing interdependencies between critical parts of the network, see Figs 2 and 4), and (4) a high pace of innovation[35] (producing uncertainties or 'unknown unknowns'). Could these developments create a "global time bomb"? (See Box 3.)

Knowledge gaps

Not well behaved

The combination of complex interactions with strong couplings can lead to surprising, potentially dangerous system behaviours[17,30], which are barely understood. At present, most of the scientific understanding of large networks is restricted to cases of special, sparse, or static networks. However, dynamically changing, strongly coupled, highly interconnected and densely populated complex systems are fundamentally different[36]. The number of possible system behaviours and proper management strategies, when regular interaction networks are replaced by irregular ones, is overwhelming[18]. In other words, there is no standard solution for complex systems, and 'the devil is in the detail'.

BOX 2

Global information and communication systems

One vulnerable system deserving particular attention is our global network of information and communication technologies (ICT)[11]. Although these technologies will be central to the solution of global challenges, they are also part of the problem and raise fundamental ethical issues, for example, how to ensure the self-determined use of personal data. New 'cyber-risks' arise from the fact that we are now enormously dependent on reliable information and communication systems. This includes threats to individuals (such as privacy intrusion, identity theft or manipulation by personalized information), to companies (such as cybercrime), and to societies (such as cyberwar or totalitarian control).

Our global ICT system is now the biggest artefact ever created, encompassing billions of diverse components (computers, smartphones, factories, vehicles and so on). The digital and real world cannot be divided any more; they form a single interweaved system. In this new "cybersocial world", digital information drives real events. The techno-socio-economic implications of all this are barely understood[11]. The extreme speed of these systems, their hyper-connectivity, large complexity, and massive data volumes produced are often seen as problems. Moreover, the components increasingly make autonomous decisions. For example, supercomputers are now performing the majority of financial transactions. The 'flash crash' of 6 May 2010 illustrates the unexpected systemic behaviour that can result (http://en.wikipedia.org/wiki/2010_Flash_Crash, accessed 29 July 2012): within minutes, nearly $1 trillion in market value disappeared before the financial markets recovered again. Such computer systems can be considered to be 'artificial social systems', as they learn from information about their environment, develop expectations about the future, and decide, interact and communicate autonomously. To design these systems properly, ensure a suitable response to human needs, and avoid problems such as co-ordination failures, breakdowns of cooperation, conflict, (cyber-)crime or (cyber-)war, we need a better, fundamental understanding of socially interactive systems.

Moreover, most existing theories do not provide much practical advice on how to respond to actual global risks, crises and disasters, and empirically based risk-mitigation strategies often remain qualitative[37–42]. Most scientific studies make idealized assumptions such as homogeneous components, linear, weak or deterministic interactions, optimal and independent behaviours, or other favourable features that make systems well-behaved (smooth dependencies, convex sets, and so on). Real-life systems, in contrast, are characterized by heterogeneous components, irregular interaction networks, nonlinear interactions, probabilistic behaviours, interdependent decisions, and networks of networks. These differences can change the resulting system behaviour fundamentally and dramatically and in unpredictable ways. That is, real-world systems are often not well-behaved.

Behavioural rules may change

Many existing risk models also neglect the special features of social systems, for example, the importance of a feedback of the emergent macro-level dynamics on the micro-level behaviour of the system components or on specific information input (see Box 4). Now, a single video or tweet may cause deadly social unrest on the other side of the globe. Such changes of the microdynamics may also change the failure probabilities of system components.

For example, consider a case in which interdependent system components may fail or not with certain probabilities, and where local damage increases the likelihood of further damage. As a consequence, the bigger a failure cascade, the higher the probability that it might grow larger. This establishes the possibility of global catastrophic risks (see

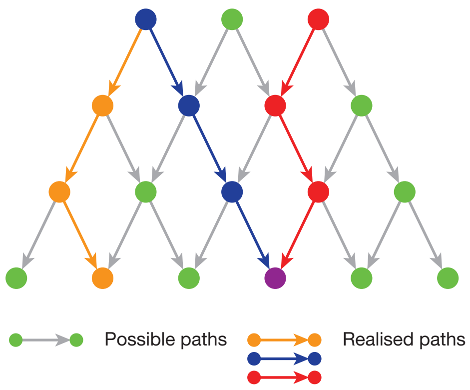


Figure 3 | Illustration of probabilistic cascade effects in systems with networked risks. The orange and blue paths show that the same cause can have different effects, depending on the respective random realization. The blue and red paths show that different causes can have the same effect. The understanding of cascade effects requires knowledge of at least the following three contributing factors: the interactions in the system, the context (such as institutional or boundary conditions), and in many cases, but not necessarily so, a triggering event (i.e. randomness may determine the temporal evolution of the system). While the exact timing of the triggering event is often not predictable, the post-trigger dynamics might be foreseeable to a certain extent (in a probabilistic sense). When system components behave randomly, a cascade effect might start anywhere, but the likelihood to originate at a weak part of the system is higher (e.g. traffic jams mostly start at known bottlenecks, but not always).

Fig. 4), which cannot be reasonably insured against. The decreasing capacity of a socio-economic system to recover as a cascade failure progresses (thereby eliminating valuable resources needed for recovery) calls for a strong effort to stop cascades right at the beginning, when the damage is still small and the problem may not even be perceived as threatening. Ignoring this important point may cause costly and avoidable damage.

Fundamental and man-made uncertainty

Systems involving uncertainty, where the probability of particular events (for example, the occurrence of damage of a certain size) cannot be specified, are probably the least understood. Uncertainty may be a result of limitations of calibration procedures or lack of data. However, it may also have a fundamental origin. Let us assume a system of systems, in which the output variables of one system are input variables of another one. Let us further assume that the first system is composed of well-behaved components, whose variables are normally distributed around their equilibrium state. Connecting them strongly may nevertheless cause cascade effects and power-law-distributed output variables[13]. If the exponent of the related cumulative distribution function is between -2 and -1, the standard deviation is not defined, and if it is between -1 and 0, not even the mean value exists. Hence, the input variables of the second system could have any value, and the damage in the second system depends on the actual, unpredictable values of the input variables. Then, even if one had all the data in the world, it would be impossible to predict or control the outcome. Under such conditions it is not possible to protect the system from catastrophic failure. Such problems must and can only be solved by a proper (re)design of the system and suitable management principles, as discussed in the following.

Some design and operation principles

Managing complexity using self-organization

When systems reach a certain size or level of complexity, algorithmic constraints often prohibit efficient top-down management by real-time optimization. However, "guided self-organisation"[32,43,44] is a promising alternative way of managing complex dynamical systems, in a decentralized, bottom-up way. The underlying idea is to use, rather than fight, the system-immanent tendency of complex systems to self-organize and thereby create a stable, ordered state. For this, it is important to have the

Table 1 | Drivers and examples of systemic instabilities

Driver/factor	Description/phenomenon	Field/modelling approach	Examples	Surprising system behaviour
Threshold effect	Unexpected transition, systemic shift	Bifurcation[73] and catastrophe theory[12], explosive percolation[25], dragon kings[26]	Revolutions (for example, the Arab Spring, breakdown of former GDR, now East Germany)	Sudden failure of continuous improvement attempts
Randomness in a strongly coupled system	Strong correlations, mean-field approximation ('representative agent model') does not work	Statistical physics, theory of critical phenomena[13]	Self-organized criticality[22], earthquakes[74], stock market variations, evolutionary jumps, floods, sunspots	Extreme events[21], outcome can be opposite of mean-field prediction
Positive feedback	Dynamic instability and amplification effect, equilibrium or stationary state cannot be maintained	(Linear) stability analysis, eigenvalues theory, sensitivity analysis	Tragedy of the commons[31] (tax evasion, over-fishing, exploitation of environment, global warming, free-riding, misuse of social benefits)	Bubbles and crashes, cooperation breaks down, although it would be better for everyone
Wrong timing (mismatch of adjustment processes)	Over-reaction, growing oscillations, loss of synchronization[51]	(Linear) stability analysis, eigenvalue theory	Phantom traffic jams[75], blackout of electrical power grids[76]	Breakdown of flow despite sufficient capacity
Strong interaction, contagion	Domino and cascade effects, avalanches	Network analysis, agent-based models, bundle-fibre model[24]	Financial crisis, epidemic spreading[8]	It may be impossible to enumerate the risk
Complex structure	Perturbations in one network affect another one	Theory of interdependent networks[4]	Coupled electricity and communication networks, impact of natural disasters on critical infrastructures	Possibility of sudden failure (rather than gradual deterioration of performance)
Complex dynamics	Self-organized dynamics, emergence of new systemic properties	Nonlinear dynamics, chaos theory[77], complexity theory[28]	Crowd turbulence[33]	Systemic properties differ from the component properties
Complex function	Sensitivity, opaqueness, scientific unknowns	Computational and experimental testing	Information and communication systems	Unexpected system properties and failures
Complex control	Time required for computational solution explodes with system size, delayed or non-optimal solutions	Cybernetics[78], heuristics	Traffic light control[45], production, politics	Optimal solution unreachable, slower-is-faster effect[75]
Optimization	Orientation at state of high performance; loss of reserves and redundancies	Operations research	Throughput optimization, portfolio optimization	Capacity drop[75], systemic risks created by insurance against risks[79]
Competition	Incompatible preferences or goals	Economics, political sciences	Conflict[72]	Market failure, minority may win
Innovation	Introduction of new system components, designs or properties; structural instability[80]	Evolutionary models, genetic algorithms[68]	Financial derivatives, new products, new procedures and new species	Point change can mess up the whole system, finite time singularity[35,81]

right kinds of interactions, adaptive feedback mechanisms, and institutional settings. By establishing proper 'rules of the game', within which the system components can self-organize, including mechanisms ensuring rule compliance, top-down and bottom-up principles can be combined and inefficient micro-management can be avoided. To overcome suboptimal solutions and systemic instabilities, the interaction rules or institutional settings may have to be modified. Symmetrical interactions, for example, can often promote a well-balanced situation and an evolution to the optimal system state[32].

Traffic light control is a good example to illustrate the ongoing paradigm shift in managing complexity. Classical control is based on the principle of a 'benevolent dictator': a traffic control centre collects information from the city and tries to impose an optimal traffic light control. But because the optimization problem is too demanding for real-time optimization, the control scheme is adjusted for the typical traffic flows on a certain day and time. However, this control is not optimal for the actual situation owing to the large variability in the arrival rates of vehicles.

Significantly smaller and more predictable travel times can be reached using a flexible "self-control" of traffic flows[45]. This is based on a suitable real-time response to a short-term anticipation of vehicle flows, thereby coordinating neighbouring intersections. Decentralized principles of managing complexity are also used in information and communication systems[46], and they are becoming a trend in energy production ("smart grids"[47]). Similar self-control principles could be applied to logistic and production systems, or even to administrative processes and governance.

Coping with networked risks

To cope with hyper-risks, it is necessary to develop risk competence and to prepare and exercise contingency plans for all sorts of possible failure cascades[4,5,14–20]. The aim is to attain a resilient ('forgiving') system design and operation[48,49].

An important principle to remember is to have at least one backup system that runs in parallel to the primary system and ensures a safe fallback level. Note that a backup system should be operated and designed according to different principles in order to avoid a failure of both systems for the same reasons. Diversity may not only increase systemic resilience (that is, the ability to absorb shocks or recover from them), it can also promote systemic adaptability and innovation[43]. Furthermore, diversity makes it less likely that all system components fail at the same time. Consequently, early failures of weak system components (critical fluctuations) will create early warning signals of an impending systemic instability[50].

An additional principle of reducing hyper-risks is the limitation of system size, to establish upper bounds to the possible scale of disaster. Such a limitation might also be established in a dynamical way, if real-time feedback allows one to isolate affected parts of the system before others are damaged by cascade effects. If a sufficiently rapid dynamic decoupling cannot be ensured, one can build weak components (breaking points) into the system, preferably in places where damage would be comparatively small. For example, fuses in electrical circuits serve to avoid large-scale damage of local overloads. Similarly, engineers have learned to build crush zones in cars to protect humans during accidents.

A further principle would be to incorporate mechanisms producing a manageable state. For example, if the system dynamics unfolds so rapidly that there is a danger of losing control, one could slow it down by introducing frictional effects (such as a financial transaction fee that kicks in when financial markets drop).

Also note that dynamical processes in a system can desynchronize[51], if the control variables change too quickly relative to the timescale on which the governed components can adjust. For example, stable hierarchical systems typically change slowly on the top and much quicker on the lower levels. If the influence of the top on the bottom levels becomes

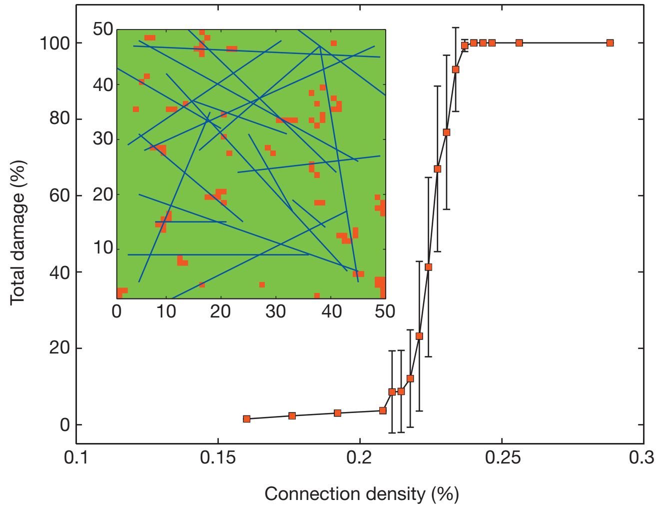


Figure 4 | Cascade spreading is increasingly hard to recover from as failure progresses. The simulation model mimics spatial epidemic spreading with air traffic and healing costs in a two-dimensional 50 × 50 grid with periodic boundary conditions and random shortcut links. The colourful inset depicts an early snapshot of the simulation with $N = 2,500$ nodes. Red nodes are infected, green nodes are healthy. Shortcut links are shown in blue. The connectivity-dependent graph shows the mean value and standard deviation of the fraction $i(t)/N$ of infected nodes over 50 simulation runs. Most nodes have four direct neighbours, but a few of them possess an additional directed random connection to a distant node. The spontaneous infection rate is $s = 0.001$ per time step; the infection rate by an infected neighbouring node is $P = 0.08$. Newly infected nodes may infect others or may recover from the next time step onwards. Recovery occurs with a rate $q = 0.4$, if there is enough budget $b > c$ to bear the healing costs $c = 80$. The budget needed for recovery is created by the number of healthy nodes $h(t)$. Hence, if $r(t)$ nodes are recovering at time t, the budget changes according to $b(t + 1) = b(t) + h(t) - cr(t)$. As soon as the budget is used up, the infection spreads explosively. (See also the movie at http://vimeo.com/53872893.)

too strong, this may impair the functionality and self-organization of the hierarchical structure[32].

Last but not least, reducing connectivity may serve to decrease the coupling strength in the system. This implies a change from a dense to a sparser network, which can reduce contagious spreading effects. In fact, sparse networks seem to be characteristic for ecological systems[52].

As logical as the above safety principles may sound, these precautions have often been neglected in the design and operation of strongly coupled, complex systems such as the world financial system[20,53,54].

What is ahead

Despite all our knowledge, much work is still ahead of us. For example, the current financial crisis shows that much of our theoretical knowledge has not yet found its way into real-world policies, as it should.

Economic crises

Two main pillars of mainstream economics are the equilibrium paradigm and the representative agent approach. According to the equilibrium paradigm, economies are viewed as systems that tend to evolve towards an equilibrium state. Bubbles and crashes should not happen and, hence, would not require any precautions[54]. Sudden changes would be caused exclusively by external shocks. However, it does not seem to be widely recognized that interactions between system elements can cause amplifying cascade effects even if all components relax to their equilibrium state[55,56].

Representative agent models, which assume that companies act in the way a representative (average) individual would optimally decide, are more general and allow one to describe dynamical processes. However, such models cannot capture processes well if random events, the diversity of system components, the history of the system or correlations between variables matter a lot. It can even happen that representative agent models make predictions opposite to those of agent-based computer simulations assuming the very same interaction rules[32] (see Fig. 2).

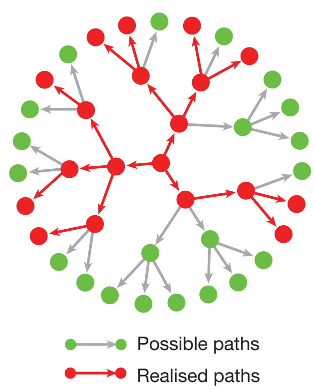
BOX 3

Have humans created a 'global time bomb'?

For a long time, crowd disasters and financial crashes seemed to be puzzling, unrelated, 'God-given' phenomena one simply had to live with. However, it is possible to grasp the mechanisms that cause complex systems to get out of control. Amplification effects can result and promote failure cascades, when the interactions of system components become stronger than the frictional effects or when the damaging impact of impaired system components on other components occurs faster than the recovery to their normal state.

For certain kinds of interaction networks, the similarity of related cascade effects with those of chain reactions in nuclear fission is disturbing (see Box 3 Figure). It is known that such processes are difficult to control. Catastrophic damage is a realistic scenario. Given the similarity of the cascading mechanisms, is it possible that our worldwide anthropogenic system will get out of control sooner or later? In other words, have humans unintentionally created something like a "global time bomb"?

If so, what kinds of global catastrophic scenarios might humans in complex societies[81] face? A collapse of the global information and communication systems or of the world economy? Global pandemics[6–9]? Unsustainable growth, demographic or environmental change? A global food or energy crisis? The large-scale spreading of toxic substances? A cultural clash[83]? Another global-scale conflict[84,85]? Or, more likely, a combination of several of these contagious phenomena (the "perfect storm"[1])? When analysing such global risks, one should bear in mind that the speed of destructive cascade effects might be slow, and the process may not look like an explosion. Nevertheless, the process can be hard to stop. For example, the dynamics underlying crowd disasters is slow, but deadly.



Box 3 Figure | Illustration of the principle of a 'time bomb'. A single, local perturbation of a node may cause large-scale damage through a cascade effect, similar to chain reactions in nuclear fission.

Paradigm shift ahead

Both equilibrium and representative agent models are fundamentally incompatible with probabilistic cascade effects—they are different classes of models. Cascade effects cause a system to leave its previous (equilibrium) state, and there is also no representative dynamics, because different possible paths of events may look very different (see Fig. 3). Considering furthermore that the spread of innovations and products also involves cascade effects[57,58], it seems that cascade effects are even the rule rather than the exception in today's economy. This calls for a new economic thinking. Many currently applied theories are based on the

BOX 4

Social factors and social capital

Many twenty-first-century challenges have a social component and cannot be solved by technology alone[86]. Socially interactive systems, be it social or economic systems, artificial societies, or the hybrid system made up of our virtual and real worlds, are characterized by a number of special features, which imply additional risks: The components (for example, individuals) take autonomous decisions based on (uncertain) future expectations. They produce and respond to complex and often ambiguous information. They have cognitive complexity. They have individual learning histories and therefore different, subjective views of reality. Individual preferences and intentions are diverse, and imply conflicts of interest. The behaviour may depend on the context in a sensitive way. For example, the way people behave and interact may change in response to the emergent social dynamics on the macro scale. This also implies the ability to innovate, which may create surprising outcomes and 'unknown unknowns' through new kinds of interactions. Furthermore, social network interactions can create social capital[43,87] such as trust, solidarity, reliability, happiness, social values, norms and culture.

To assess systemic risks fully, a better understanding of social capital is crucial. Social capital is important for economic value generation, social well-being, and societal resilience, but it may be damaged or exploited, like our environment. Therefore, humans need to learn how to quantify and protect social capital[36]. A warning example is the loss of trillions of dollars in the stock markets during the financial crisis, which was largely caused by a loss of trust. It is important to stress that risk insurances today do not consider damage to social capital. However, it is known that large-scale disasters have a disproportionate public impact, which is related to the fact that they destroy social capital. By neglecting social capital in risk assessment, we are taking higher risks than we would rationally do.

BOX 5

Beyond current risk analysis

State-of-the-art risk analysis[88] still seems to have a number of shortcomings. (1) Estimates for the probability distribution and parameters describing rare events, including the variability of such parameters over time, are often poor. (2) The likelihood of coincidences of multiple unfortunate, rare events is often underestimated (but there is a huge number of possible coincidences). (3) Classical fault tree and event tree analyses[37] (see also http://en.wikipedia.org/wiki/Fault tree analysis and http://en.wikipedia.org/wiki/Event tree, both accessed 18 November 2012) do not sufficiently consider feedback loops. (4) The combination of probabilistic failure analysis with complex dynamics is still uncommon, even though it is important to understand amplification effects and systemic instabilities. (5) The relevance of human factors, such as negligence, irresponsible or irrational behaviour, greed, fear, revenge, perception bias, or human error is often underestimated[30,41]. (6) Social factors, including the value of social capital, are typically not considered. (7) Common assumptions underlying established ways of thinking are not questioned enough, and attempts to identify uncertainties or 'unknown unknowns' are often insufficient. Some of the worst disasters have happened because of a failure to imagine that they were possible[42], and thus to guard against them. (8) Economic, political and personal incentives are not sufficiently analysed as drivers of risks. Many risks can be revealed by looking for stakeholders who could potentially profit from risk-taking, negligence or crises. Risk-seeking strategies that attempt to create new opportunities via systemic change are expected mainly under conditions of uncertainty, because these tend to be characterized by controversial debates and, therefore, under-regulation.

To reach better risk assessment and risk reduction we need transparency, accountability, responsibility and awareness of individual and institutional decision-makers[11,36]. Modern governance sometimes dilutes responsibility so much that nobody can be held responsible anymore and catastrophic risks may be a consequence. The financial crisis seems to be a good example. Part of the problem appears to be that credit default swaps and other financial derivatives are modern financial insurance instruments, which transfer risks from the individuals or institutions causing them to others, thereby encouraging excessive risk taking. It might therefore be necessary to establish a principle of collective responsibility, by which individuals or institutions share responsibility for incurred damage in proportion to their previous (and subsequent) gains.

assumption that statistically independent, optimal decisions are made. Under such idealized conditions one can show that financial markets are efficient, that herding effects will not occur, and that unregulated, self-regarding behaviour can maximize system performance, benefiting everyone. Some of these paradigms are centuries old yet still applied by policy-makers. However, such concepts must be questioned in a world where economic decisions are strongly coupled and cascade effects are frequent[54,59].

Global Systems Science

For a long time, humans have considered systemic failures to originate from 'outside the system', because it has been difficult to understand how they could come about otherwise. However, many disasters in anthropogenic systems result from a wrong way of thinking and, consequently, from inappropriate organization and systems design. For example, we often apply theories for well-behaved systems to systems that are not well behaved.

Given that many twenty-first-century problems involve socio-economic challenges, we need to develop a science of economic systems that is consistent with our knowledge of complex systems. A massive interdisciplinary research effort is indispensable to accelerate science and innovation so that our understanding and capabilities can keep up with the pace at which our world is changing ('innovation acceleration'[11]).

In the following, I use the term Global Systems Science to emphasize that integrating knowledge from the natural, engineering and social sciences and applying it to real-life systems is a major challenge that goes beyond any currently existing discipline. There are still many unsolved problems regarding the interplay between structure, dynamics and functional properties of complex systems. A good overview of global interdependencies between different kinds of networks is lacking as well. The establishment of a Global Systems Science should fill these knowledge gaps, particularly regarding the role of human and social factors.

Progress must be made in computational social science[60], for example by performing agent-based computer simulations[32,61–63] of learning agents with cognitive abilities and evolving properties. We also require the close integration of theoretical and computational with empirical and experimental efforts, including interactive multi-player serious games[64,65], laboratory and web experiments, and the mining of large-scale activity data[11].

We furthermore lack good methods of calculating networked risks. Modern financial derivatives package many risks together. If the correlations between the components' risks are stable in time, copula methodology[66] offers a reasonable modelling framework. However, the correlations strongly depend on the state of the global financial system[67]. Therefore, we still need to learn how realistically to calculate the interdependence and propagation of risks in a network, how to absorb them, and how to calibrate the models (see Box 5). This requires the integration of probability calculus, network theory and complexity science with large-scale data mining.

Making progress towards a better understanding of complex systems and systemic risks also depends crucially on the collection of 'big data' (massive amounts of data) and the development of powerful machine learning techniques that allow one to develop and validate realistic explanatory models of interdependent systems. The increasing availability of detailed activity data and of cheap, ubiquitous sensing technologies will enable previously unimaginable breakthroughs.

Finally, given that it can be dangerous to introduce new kinds of components, interactions or interdependencies into our global systems, a science of integrative systems design is needed. It will have to elaborate suitable interaction rules and system architectures that ensure not only system components to work well, but also favourable systemic interactions and outcomes. A particular challenge is to design value-sensitive information systems and financial exchange systems that promote awareness and responsible action[11]. How could we create open information platforms that minimize misuse? How could we avoid privacy intrusion and the manipulation of individuals? How could we enable greater participation of citizens in social, economic and political affairs?

Finding tailored design and operation principles for complex, strongly coupled systems is challenging. However, inspiration can be drawn from ecological[52], immunological[68], and social systems[32]. Understanding the principles that make socially interactive systems work well (or not) will facilitate the invention of a whole range of socio-inspired design and operation principles[11]. This includes reputation, trust, social norms, culture, social capital and collective intelligence, all of which could help to counter cybercrime and to design a trustable future Internet.

New exploration instruments

To promote Global Systems Science with its strong focus on interactions and global interdependencies, the FuturICT initiative proposes to build new, open exploration instruments ('socioscopes'), analogous to the telescopes developed earlier to explore new continents and the universe. One such instrument, called the "Planetary Nervous System"[11], would process data reflecting the state and dynamics of our global techno-socio-economic-environmental system. Internet data combined with data collected by sensor networks could be used to measure the state of our world in real time[69]. Such measurements should reflect not only physical and environmental conditions, but also quantify the "social footprint"[11], that is, the impact of human decisions and actions on our socio-economic system. For example, it would be desirable to develop better indices of social wellbeing than the gross domestic product per capita, ones that consider environmental factors, health and human and social capital (see Box 4 and http://www.stiglitz-sen-fitoussi.fr and http://www.worldchanging.com/archives/010627.html). The Planetary Nervous System would also increase collective awareness of possible problems and opportunities, and thereby help us to avoid mistakes.

The data generated by the Planetary Nervous System could be used to feed a "Living Earth Simulator"[11], which would simulate simplified, but sufficiently realistic models of relevant aspects of our world. Similar to weather forecasts, an increasingly accurate picture of our world and its possible evolutions would be obtained over time as we learn to model anthropogenic systems and human responses to information. Such 'policy wind tunnels' would help to analyse what-if scenarios, and to identify strategic options and their possible implications. This would provide a new tool with which political decision-makers, business leaders, and citizens could gain a better, multi-perspective picture of difficult matters.

Finally, a "Global Participatory Platform"[11] would make these new instruments accessible to everybody and create an open 'information ecosystem', which would include an interactive platform for crowd sourcing and cooperative applications. The activity data generated there would also allow one to determine statistical laws of human decision making and collective action[64]. Furthermore, it would be conceivable to create interactive virtual worlds[65] in order to explore possible futures (such as alternative designs of urban areas, financial architectures and decision procedures).

Discussion

I have described how system components, even if their behaviour is harmless and predictable when separated, can create unpredictable and uncontrollable systemic risks when tightly coupled together. Hence, an improper design or management of our global anthropogenic system creates possibilities of catastrophic failures.

Today, many necessary safety precautions to protect ourselves from human-made disasters are not taken owing to insufficient theoretical understanding and, consequently, wrong policy decisions. It is dangerous to believe that crises and disasters in anthropogenic systems are 'natural', or accidents resulting from external disruptions. Another misconception is that our complex systems could be well controlled or that our socio-economic system would automatically fix itself.

Such ways of thinking impose huge risks on society. However, owing to the systemic nature of man-made disasters, it is hard to blame anybody for the damage. Therefore, classical self-adjustment and feedback mechanisms will not ensure responsible action to avert possible disasters. It also seems that present law cannot handle situations well, when the problem does not lie in the behaviour of individuals or companies, but in the interdependencies between them.

The increasing availability of 'big data' has raised the expectation that we could make the world more predictable and controllable. Indeed, real-time management may overcome instabilities caused by delayed feedback or lack of information. However, there are important limitations: too much data can make it difficult to separate reliable from ambiguous or incorrect information, leading to misinformed decision-making. Hence too much information may create a more opaque rather than a more transparent picture.

If a country had all the computer power in the world and all the data, would this allow a government to make the best decisions for everybody? Not necessarily. The principle of a caring state (or benevolent dictator) would not work, because the world is too complex to be optimized top-down in real time. Decentralized coordination with affected (neighbouring) system components can achieve better results, adapted to local needs[45]. This means that a participatory approach, making use of local resources, can be more successful. Such an approach is also more resilient to perturbations.

For today's anthropogenic system, predictions seem possible only over short time periods and in a probabilistic sense. Having all the data in the world would not allow one to forecast the future. Nevertheless, one can determine under what conditions systems are prone to cascades or not. Moreover, weak system components can be used to produce early warning signals. If safety precautions are lacking, however, spontaneous cascades might be unstoppable and become catastrophic. In other words, predictability and controllability are a matter of proper systems design and operation. It will be a twentyfirst-century challenge to learn how to turn this into practical solutions and how to use the positive sides of cascade effects. For example, cascades can produce a large-scale coordination of traffic lights[45] and vehicle flows[70], or promote the spreading of information and innovations[57,58], of happiness[71], social norms[72], and cooperation[31,32,59]. Taming cascade effects could even help to mobilize the collective effort needed to address the challenges of the century ahead.

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