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An urgent call to get better prepared for unexpected events

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Jurgen Spaanderman, January 2018

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Abstract:
This paper is an urgent call to get better prepared for unexpected events. The increasing spread of information technology in society leads to more complexity and non-linear behavior in the economic and financial system, and to more unpredictable, sudden events. This paper examines how people deal with non-linear behavior of systems, by looking at how we prepare for disruptive events in the economy and wider society, and it shows why we have a hard time dealing with non-linearities. The paper provides suggestions to improve our handling of non-linear system behavior for both better preparedness for disruptive events and better design of more resilient systems. A different approach to economic modelling is needed, away from equilibria thinking toward the realm of evolutionary complex adaptive systems. The paper is relevant to policymakers and decision makers who deal with long-term risk and uncertainty, and to those who want to improve their understanding of disruptive events. The ideas brought together in this paper come from various disciplines and mostly do not reflect mainstream economic thinking.

Contents

Executive summary

The central question of this paper is why many people experience disruptive events as unexpected. It covers both events beyond our imagination and events for which people misjudge risk. This subject relates to the recent shocks in the financial markets but applies equally to other systems people develop. The question is relevant to DNB as information technology seems to have an ever-increasing impact on the economy and the financial sector in particular.

There are strong indications that the impact of the posed question is increasing because the world is becoming more complex. This is reinforced by networked information technology. People are connected through networks which open up new ways to launch emerging ideas, in a decentralized manner, to cooperate with anyone in the world. Information technology finds its way into a growing number of new and existing applications, including finance, transportation, health care and education, due to the exponential growth of computer power and a continuing decrease in cost per unit operation. The evolving technologies are having a firm impact on the existing, centrally governed businesses and institutions, also in the financial markets. These networked technologies spread an increase in dynamics and non-linearities in our systems, resulting in more unexpected events, unless we better understand the dynamics and change our systems and models to be better prepared to cope with these dynamics.

Answers to the question of why many people experience disruptive events as unexpected, are found in the way our brain functions, in how we deal with probability, risk and uncertainty, and limitations in imagining long-term negative and positive consequences. Understanding a system and understanding the risks to the system as a whole, turns out to be less obvious than often thought. In particular mainstream economic models prove to be of little help in economic and financial crises, as such dynamics can either not be handled by the models or are made impossible by their assumptions.

We therefore cannot rely too much on such models and additionally need models that can cope with the complexity of the economy. Our educational system reinforces such shortcomings. People are less in control than they usually think they are because of the complexity of systems, and they are badly prepared for unexpected events because they have difficulty understanding them and little practice with modelling and experimenting with such events. There is growing interest in introducing complexity theory to model economic interactions, which allows us to model disruptive events and other non-linear behavior of systems.

As unexpected events pose a problem, suggestions are made for applying different models and to get better prepared for such events. It starts with awareness of the non-linear behavior of systems and acceptance of being less in control than people wish. It requires different behavior and different modeling. Where mainstream models assume tendency to equilibrium, we should give much more attention to models that consider the economy as a complex adaptive system, in order to better analyzing dynamics of interactions at the edge of order and chaos. This idea is not new, though complexity thinking in economics has still not been widely accepted. Moreover, technological and economic developments seem to follow a kind of evolutionary formula, including “differentiate, select and amplify”, forming an adapting mechanism to avoid being disrupted. As networked information technology seems to pose higher risk to more and faster propagating errors and attacks, the sensitivities of network applications needs to be better protected requiring a kind of immune system to make them resilient, preferably even stronger, when attacked.

Thinking in complexity and non-equilibrium models requires firm changes in the way people work, the models they use and the skills they need. It is an open question how today's centralized governance model and national legislation are able to handle the increasing global dynamics and emergence of new technological applications because of their rapid global growth and disruption of existing structures. Centralized governance and control may need to be replaced progressively by decentralized models with inherent robustness and stochastic trust. Finally, economic educational programs have to further adapt, as an alternative to traditional equilibrium thinking, towards complex adaptive system thinking, recognizing the non-linear adaptive behavior with emergent and critical patterns that may arise. This would bring knowledge, experience and tools to get better prepared for sudden systemic changes and unexpected events.

1 Introduction

Usually people take life as if it were on a rather constant speed, in need for routine and assuming the next day of our life and environment will be similar to today. Handling change is a challenge for people. The possibility that tonight the world may be hit by a meteorite or large volcano eruption, suddenly destroying the basic conditions required for life, is usually not taken into account. Often changes either for better or for worse are underestimated, because extrapolations usually follow, unconsciously, a linear path. Fat-tail risks have been heavily underestimated as we learned during the recent financial crisis. The measures taken, such as higher financial buffers for banks, stress tests and more centralized control, are mostly meant to decrease the likelihood and impact of a similar crisis happening again, i.e. usually a linear extrapolation of what we had. Most likely the next financial crisis will be different. The same holds for unanticipated terrorist attacks, which were followed up by measures related to the event that had just occurred, such as more security at airports and increased security at buildings to better protect against a similar attack. More of the same along a linear imagination. Humans are barely able to anticipate events on a non-linear scale. Non-linearity means that the effect is not proportional to the cause. Nature however mostly evolves in a non-linear manner, via power laws and S-curves, as well as sudden discrete changes called phase transitions.

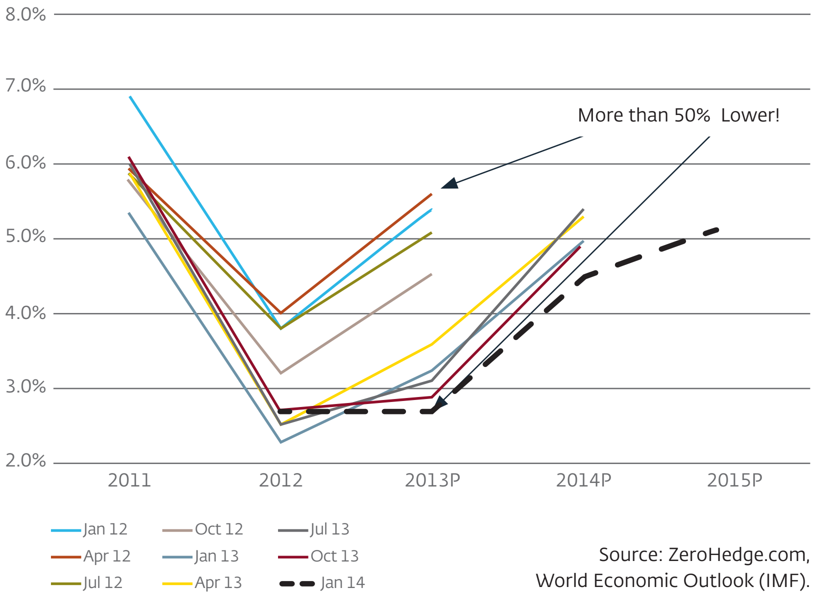
1.1 The subject of discussion

The focus of this paper is on the question of why people often experience disruptive events as unexpected, why this is a problem, and what we can do about it. The question is relevant to DNB as the growing influence of information technology on the financial system causes more complex dynamics that are likely to cause more disruptive events. Digitization of products and its fast and wide spread through information networks cause a dynamic of complexity with power laws and exponentials. These technologies are called exponential because of their accelerating growth and impact on society, including the financial sector. Banking is rapidly changing into IT business. Technology is transforming the payments and settlement business into a system with tightly coupled interactions and interdependencies that provide us with instant services, but also exhibit complex dynamics including the risk of disruptions. It is important for DNB to understand the dynamics caused by exponential technologies as well to understand how we deal with sudden changes they may cause. The paper is relevant to policy makers and decision makers who deal with long-term risk and uncertainty, and to those who want to improve their understanding and grip on disruptive events. The ideas brought together come from various disciplines and do mostly not fit mainstream economic thinking which may confront the reader but is meant to show a different view.

Sudden major and disturbing events, both in nature and in human-created systems, seem to arrive to people as surprises, leaving us overwhelmed. Examples are the recent financial crisis and other financial crises before; but also cyber-attacks; a terrorist attack; an announcement of a serious disease; long-term negative effects of food (cigarettes, too much sugar); global impact of pollution; a flood like in New Orleans; an accident at a nuclear or chemical plant or a nuclear disaster like Fukushima. Such disruptive events have low probability. In some cases, the event is indeed beyond our imagination and unexpected. In other cases, we did imagine the event, we studied the probability, decided to either act or not, followed by the acceptance of the residual risk. But what does accepting residual risk mean? Still, when the event happens, many react as if it were unexpected, as if the acceptance of the residual risk has been neglected or forgotten. It could well be that magnitude or timing are beyond our imagination, that the event has been imagined, but the risk been underestimated.

Chart 1.1 Example of underestimation: multiple revisions of IMF's world trade volume forecasts

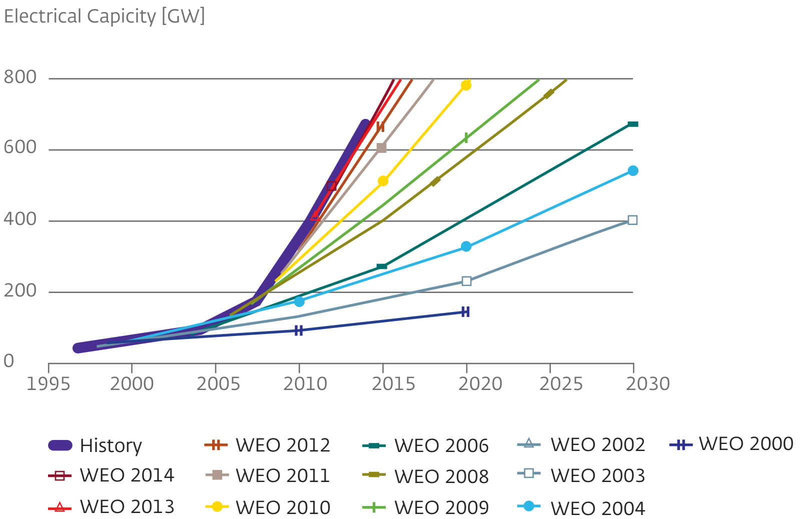
IMF's Revisions Of World Trade Volume



Source: ZeroHedge.com,
World Economic Outlook (IMF).

Whether it is economic growth, IT projects, market adoption of solar panels, and the like, we seem to underestimate the range of forecasting uncertainty, resulting in forecasting errors. Illustrative examples on forecasting errors are shown in chart 1.1 on the IMF's trade forecasts and chart 1.2 on successive projections of additions to electric capacity by renewables (mainly photo voltaic and wind) taken from the World Energy Outlook publications from the International Energy Agency (IEA).It also puts in perspective the day-to day discussion of economists, politicians, financials markets experts and project steering boards on fine-tuning prediction in fractions of a percentage,

Chart 1.2 Example of underestimation: successive IEA World Energy Outlook projections of growth in Electric Capacity by renewable energy sources



Source: EnergyWatchGroup.org, World Energy Outlook (IEA).

whereas these charts show errors of 50% and more. Another example is given by Loungani (2001). At the IMF he analyzed the performance of consensus forecasts of annual average real GDP growth, from international institutions and from the private sector, based on a dataset from 63 countries over the period 1989-1998. He found that only two of the 60 recessions that occurred over the sample were predicted a year in advance. In October the extent of a recession in that year (so within 2 months) was underestimated in 50 out of 60 cases. He also found that private sector forecasts and those of international organizations are rather similar with forecast errors correlation of 0.9 or better. Why do these forecasts collectively fail? Could it be the limitations in the models and the related assumptions? How do the models cope with the dynamics and non-linearity of real-life disturbances? Do we assume too often normal distributions and a tendency to equilibrium states?

In situations where we consciously accepted residual risk to an extreme event, we often get surprised when such an extreme event happens. Take the calculated probability of 1 event to happen in 10,000 years, for a flood or nuclear plant disaster; such disaster could happen tomorrow but many believe it won't happen during their lifetime. As we took measures and the residual risk is accepted and remembered as being very small, we seem to misinterpret that it is not likely going to occur any time soon. And if our estimate was off, the extreme event may happen a few times in 40 years. The same with floods: when costly measures are taken we tend to forget the likelihood remains and potentially tomorrow a flood may affects millions of people. Another illustration is the surprise stock market crash of the late 1990s, three years after that, Federal Reserve chairman Greenspan warned the market with the phrase 'irrational exuberance', referring to a mindset that occurs during speculative bubbles. It seems we are even taken by surprise after being warned.

This paper seeks explanations for our negligence, underestimation and difficulty we face with disruptive events and non-linear system behavior. Questions arise about what the reason could be for underestimation and not foreseeing disruptive events. Are we not able to imagine sudden changes and other non-linearity? Or if we can imagine, are we not willing to take negative major events properly into account? Would that be caused by psychological biases? Is it the way our brain functions that we underestimate the likelihood and impact of big events? How do we actually handle risk, probability and uncertainty? Do we use the right models for calculating risk and calculating forecasts? What is the role of education? Finding answers to these questions is important to get better informed about and prepared for disruptive events.

Answers are also urgently needed as the world seems to get more complex, which may be caused by an increasing importance of information technology and interconnectedness in society.

In summary this paper aims:

- To analyze the growing impact of information technology as a cause of non-linear system behavior;
- To clarify why people often experience disruptive events as unexpected;
- To look at how we can better understand and prepare for non-linear behavior and disruptive events.

1.2 Approach and limitations

The chosen approach in the paper is multidisciplinary, mixing views from physics, information technology, biology, psychology and economics It connects various views from the literature in order to get a broad view of possible explanations as to why people often experience disruptive events as unexpected. The paper presents different and intentionally sometimes provocative thoughts, away from mainstream thinking, believed to be necessary to improve our bad track record of forecasting and preparedness for disruptive events.

Chapter 2 starts with the observation that the world is getting more complex and it investigates the dynamics that new technologies cause in society. Information technology leads towards an acceleration in our systems causing various dynamics and unpredictable events. The impact of dematerialization of products and the transitions to network-based information services is discussed as well as the changing dynamics between consumers and producers that allow for faster and wider distribution via platforms, at ever lower costs. The technological innovation shows exponential progression which will cause more non-linear behavior in the economy which are likely to have profound implication on the financial sector.

Chapter 3 presents a variety of possible answers to the central question of why we often experience disruptive events as unexpected. It is an attempt to find the main causes. It looks at the difficulties our brain has in imagining non-linear system behavior and also to deal with it, our tendency to provide quick answers and our tendency to extrapolate in linear ways while many systems (we built) have non-linear characteristics. Dealing with probability presents another challenge to our brain. This chapter further looks at the way people deal with risk and risk models, and how uncertainty is handled. Finally, limitations of economic modelling are discussed as one of the causes of unpreparedness to disruptive events, supplemented with a preview of complexity thinking in economics. The non-linearity of the dynamics caused by the exponential technologies as described in chapter 2 makes the need for better modelling and preparedness to disruptive events more urgent and important.

Chapter 4 provides suggestions for such modelling as an answer to the findings of chapter 2 and 3. It briefly explains the characteristics of complex adaptive systems and shows the better fit with human behavior and propagation of technology in society. Complexity recognizes that the interactions in our economy tend more to the edge of chaos rather than seeking a state of equilibrium. Examples are provided of complexity models. Further, similarities are shown between a generic evolutionary process and economic developments from which ideas and services emerge, resulting into an evolutionary complex adaptive system. Given the dynamics of networks and complex behavior of systems, guidance is provided for better dealing with non-linear system behavior to improve resilience, based on other complex systems. This chapter ends with suggestions to use these techniques to improve the design and resilience of our financial infrastructures.

Chapter 5 provides the conclusions of the paper.

2 Disruptive impact of technologies

It seems the world is getting more complex. The rapid advances of information technology (IT) through networks show an exponential curve of expansion. Sectors like finance, transportation, energy, health care and education have been transformed, and these technologies change the structure and interaction in society and affect our institutions. In general this leads to services that are more accessible and cheaper, but the dynamics in systems increase and show more chaotic behavior. Ignoring such characteristics will result in more surprises about disruptive events, non-linear behavior and unforeseen risk. This implies that the misconception about and overreliance on oversimplified models that misguide us when we need them the most, will become even more pressing.

2.1 Exponential technologies

Evolution, technology and complexity
People experience an increase in complexity in the world. Evolution and interconnectedness play a key role in this process as the evolutionary path of development moves from simple to more complicated. Life started with simple single-celled organisms, called prokaryote, followed by the more advanced eukaryote and then multicellular lifeform, exhibiting increasing complexity. Similarly, the birth of more complicated atoms developed in the course of time, from the simplest atoms just after the big bang.
In general, on a time scale diagram going to the right towards more complex seems unlimited, while going back to simpler is limited. Illustrative is any development of a physical quantity expressed in a diagram (y-ax) with time on the horizontal ax, showing too late is open-ended, versus too early is limited (fastest possible speed; or ultimately the y-ax itself) and similarly, more complicated is open-ended while simplifying is limited. Examples from daily life are a flight and a project. A flight can arrive some time earlier, but that is physically limited, whereas delay is in principle unlimited. The same applies to

finishing a project on time and clarifies why many projects become delayed: possibilities to simplify a project is rather limited whereas possibilities to make it more complicated or deviate from a plan, is nearly open ended.

It is the same with technology. Our technology becomes ever more complicated, it builds on top of earlier developments. The increase of networked technologies that make us more interconnected, with easier access to more people, ideas and knowledge and at higher speed creates order at a higher level, but the whole system is more complex. Right after Darwin's publication On the Origins of Species, Samuel Butler wrote Darwin among the Machines in which he explored the possibility that machines go through a kind of mechanical life with constant evolution and voiced his fear that humans are becoming subservient to machines that eventually would take over. Kelly (2010) calls Homo sapiens a tendency, not an entity, a process of evolution like any other living organism. He recalls that technology is not exclusively used by humans and technology has a transforming power. He continues that technology is subject to the same mechanisms and forces in the natural world that drives change. He calls progress the 'reordering of the material world that is made possible by the flows of energy and the expansion of intangible minds' and sees evolution marching towards more complexity and order. Evolution is a process of continuous innovation. Kelly puts us subordinate to the evolutionary processes, like technology has its own power and will and calls for humans to channel technology in the right direction, but at the same time he states that we are quite powerless to technological evolution.

Studies by Prigogine and Stengers (1997), brought into relation with networks by Hinssen (2014), show that in a system powered by an energy source (Earth bathed in light and heat from the Sun) structures could evolve, become more complex and thrive. Order may emerge from disorder through a process of spontaneous self-organization. Other conclusions are 1) that a system in equilibrium lacks the internal dynamics to respond to its environment and will slowly die; 2) a system in chaos ceases to function as a system; 3) the most productive state seems to be at the edge of chaos. That's where there is maximum variety and creativity, leading to new possibilities and the best chance for survival. Along the same line Arthur (2009) views innovation as a result of the combination and the evolution of complementary technologies; breakthroughs come from combining new technological components in a novel way. His search for the nature of technology starts with Butler and Schumpeter and build a whole theory of how components of technology are used to create new ones. Each invention builds on former ones, rather smoothly, until the time that marginal gains do not add much anymore and a paradigm shift appears (a new S-curve). Innovation follows an evolutionary path and makes the world more complex.

How does it impact humanity? Kurzweil (2005) shows that technology develops at an exponential curve. He extrapolates the rapid technological advancement to a point of singularity for mankind, which is the point where our self-created technology is as smart as us and would continue exponentially developing itself beyond our (mental) capacity. Kurzweil, together with Diamandis (2012), set up Singularity University to study and teach the exponential technologies in a multidisciplinary setting, and to apply the developments of these exponential technologies to create an abundant future. While Kurzweil voices the prosperity technological advances will bring to us, Joy (2000) warns us of evil and disaster once the robots we develop become superior. Our possibilities to change nature presents many ethical questions about what life is and the risks we take when manipulating life. Joy's concern is that when genetic engineering is abused (by the military, accidentally or through a deliberate terrorist attack) it will create a white plague. Of course this holds for any technological advance, such as nuclear technology, which has destructive and constructive applications. Fear and

22 abuse of new technologies are old as history, like McWilliams (2015) refers to More's Utopia for a timeless warning about modern mobile technology, which might corrode people's self-government, freedom and traditions without them being conscious. Our belief in technological progress has peaked several times before. In the 19th and 20th century technology brought us electrical light, telephony, radio communication, cars, mass production, jobs, income and less inequality. For example the discovery of radioactivity and nuclear fission at the end of the 19th century led to an overly optimistic view on this technology and applications with radioactivity were introduced in people's regular lives without them being aware of the dangers and health risks of radioactivity. After several accidents, common sense returned and people became more careful with the new technology. Each time we have to find ways to handle new technology, to answer the ethical question and provide the right protection to all actors in society. The expansion of technology and the increase of complexity put our belief to be in control firmly in perspective. We and our technology seem to be part of the process of an increasingly complex world that seeks the edge of chaos and could arrive through emergence into new states of order. It makes the issue of disruptive events and our shortcomings to prepare for them even more urgent.

Shannon, Moore's law and the accelerating adoption of exponential technology

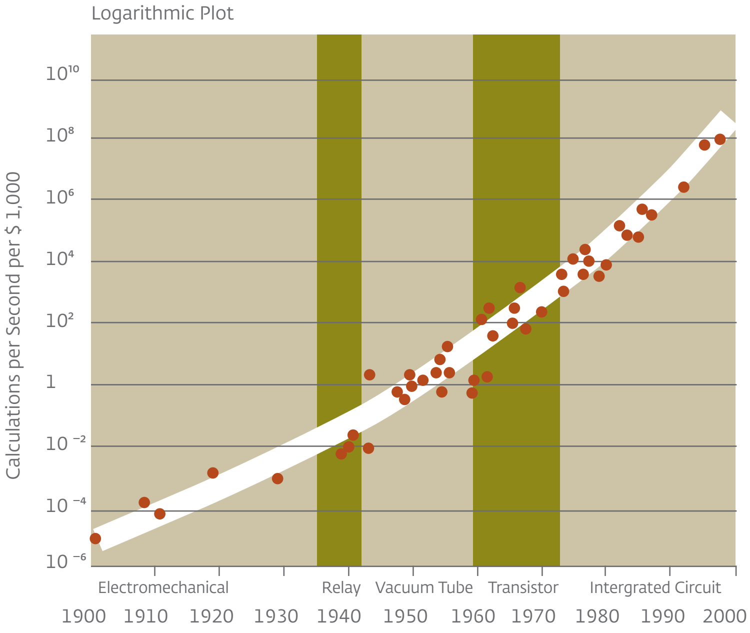
Technology started to develop even more rapidly with the arrival of information theory, of which Shannon (1948) is seen as the father. He proved the feasibility of a digital circuit, around the time the first transistor was created. Shannon than invented the bit and defined the theory of coding and transmitting digital signals. He described how to deal with uncertainty in the digital transmission as well as the rules for accurate transmission of information. These elements together allowed for transforming analogue signals into digital ones and transmitting them. Without these inventions we would be without smartphones, digital data services and computers, and hardly able to model complex networks. It was the start of digitizing analogue signals, messages, music and video that used to be available in analogue signals on a tangible medium. Digitization means transforming it into digital representation. Once the technology allows to digitize a product or service, it opens new ways of processing, appearance, distributions, usually at much lower cost. The digitization typically transforms not only the product, but also the business process, the company and potentially a whole industry; this we call the digitalization of a business or process.

The information theory brought us computer chips for fast calculation and data communication. Kurzweil (2005) puts the arrival of integrated circuits in a broader perspective of technological development, i.e. after the electromechanical applications, the relay, the vacuum tube and the single transistor. He shows that these five technologies allowed for a continuous increase of calculations per second per unit cost, and that this increase is an exponential, i.e. a curve on a log scale, see chart 2.1.

The curve follows Moore's Law and actual already did before Moore (1965) observed that one could squeeze twice as many transistors on an integrated circuit every 24 months (later an 18 month period showed a better fit). Electronic circuits for computation chips get smaller and the chip's performance goes up as the rate of executing computer instruction (clock speed) increases as well, see chart 2.2. It did so over the last 5 decades and is now reaching atomic level. Moore's Law is an empirical trend rather than a law. It is not inevitable but rather a business plan to stay on this trend: the industry has set their goals to deliver computer chips to comply with Moore's law.

Chart 2.1 Kurzweil's five paradigms of technology of the last century

Moore's Law, The Fifth Paradigm

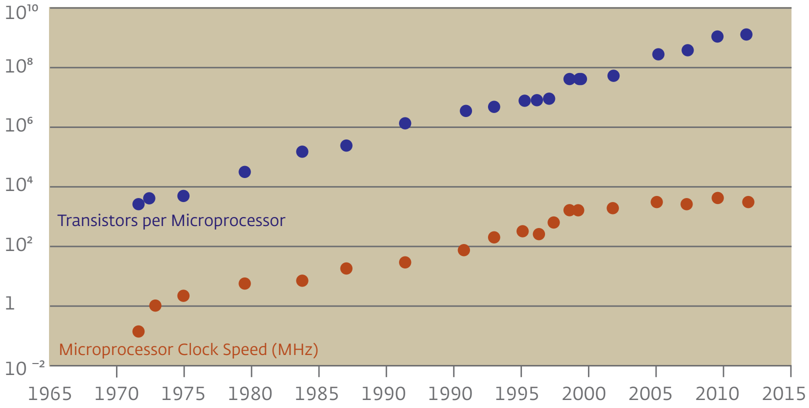


Source: Kurzweil.

Several times Moore's Law has been declared as coming to an end, but the industry managed to overcome major hurdles and further miniaturized the transistors. In the strict sense, the number of transistors on a microprocessor is indeed limited due to the limits of physical size, heat dissipation and quantum uncertainties that make smaller transistors at a certain point unreliable or impossible. Limitations could be worked around by changing the method of improving performance, such as building vertical chips (3D chips). Therefore

Chart 2.2 Moore's Law, transistors per microprocessor and clock speed (MHz)

Moore's Law



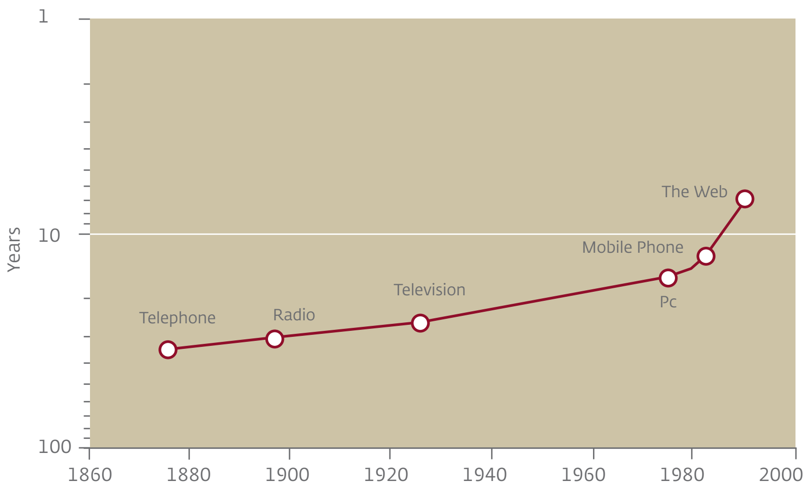
Source: Kurzweil, Intel, Berndt.

Moore's Law now has a slightly wider interpretation, not necessarily more transistors per surface, but to continue improving processing power at ever lower cost. This could extend the promise of faster and smaller for another decade. Besides, as Moore's Law is rather a business plan and so much money and knowledge invested in searching for increasing performances, as well as the firm demand for more computer power at lower unit cost, the trend is unlikely to stop any time soon. New kinds of technologies and architectures are being researched and developed that could continue the trend of faster, smaller and cheaper. Optical computing, i.e. switching light instead of electrons, promises delivering even smaller and faster computer circuits. It has additional benefits such as less disturbance in a circuit, less energy consumption and the possibility of switching parallel streams of information. Another promising development is quantum computing technology. It forms a different computer architecture, requiring different software, could be very fast in solving certain types of problems. According to Singularity University the primary applications are likely AI, cryptography, financial modelling, molecular modelling, weather forecasting and particle physics. The first three directly relevant to the financial sector. Quantum computing could be the sixth paradigm in chart 2.1.

To go back to these successive paradigms, they show the principle of exponential technologies as they follow an exponential growth path by doubling in performance every period and continuing that growth by building developments on top of one another. Each paradigm is an S-curve building on top of the next one. Kurzweil identified here an important and fundamental property of technology that when you shift to an information-based environment, the pace of development jumps onto an exponential growth path and price/performance doubles every year or two. According to Kurzweil (2005, p.3, p.491) 'Evolution applies positive feedback in that the more capable methods resulting from one stage of evolutionary progress are used to create the next stage'. In other words each generation of technology builds on the advances of previous generations, thus improvements in technology enable the next generation of even better technology, positive feedback loop. This fits the views on innovation by Kelly (2010) and Arthur (2009) expressed before. The same idea holds in terms of intelligence: intelligence creates technology and technology further improves our intelligence. Artificial Intelligence (AI) accelerates this process. AI is teachable software, it learns by means of labelled examples and improves, therefore looks intelligent for the task for which it has been developed. AI represents our increased intelligence through the tools we develop, resulting in an (exponential) increase of human intelligence. Incorporated in our biology, the technology changes us as a species. Kurzweil (2005) shows on a logarithmic scale the accelerating acceleration of adoption of new technologies, see chart 2.3.

Chart 2.3 Accelerating adoption of new technologies

Mass Use of Inventions, Years until use by 25% of US Population



Source: Kurzweil, FCC, Census.

Networks and features

Shannon and Moore's law led to digitization, increase in performance, at lower unit cost, but it is not the only explanation of the exponential growth curve of new technologies. Another explanation is the network. People are more connected than ever. A network is a set of vertices (or nodes) with edges (connections), be it a social network, computer network or road network. Some of these networks are centrally planned, like motorways, others are created without a grand plan like social networks and the World Wide Web. Networked connections have been out there for a long time, people have always had connections but the arrival of data communication, internet and the liberalization of the telecom markets boosted the impact of positive network externalities resulting in firm increase of size, reach and use, as well as quality and speed. Newman (2003) provides a great overview of networks and a review of work on the structure and function of network systems. He distinguishes technical networks, biological networks, information networks and social networks and he describes their properties, features and the processes taking place on networks. He also reviews work on sudden changes like phase transitions on networks and dynamical systems on networks. His main observation is that networks are generally far from random and actually have distinctive statistical signatures. Still more work has to be done as he sees the techniques for analyzing networks are more or less a grab-bag of miscellaneous and largely unrelated tools. More sophisticated models of networks need to be developed, in order to better understand the behavior and function of the networked systems around us.

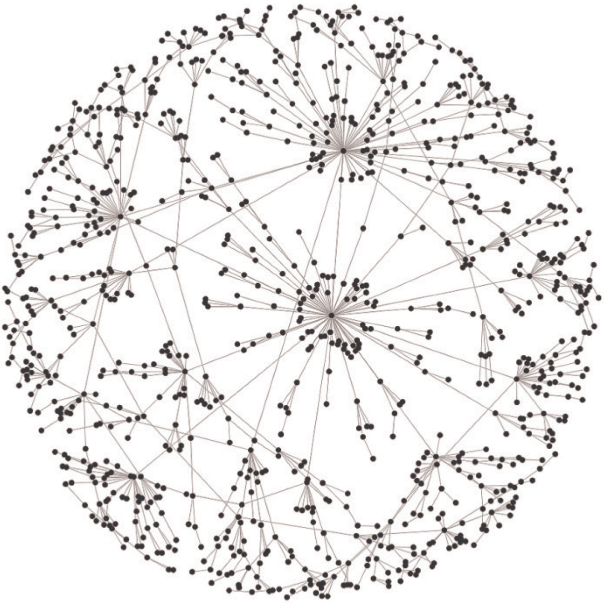
By 2020 we will be close to 7 billion connected people. That means 7 billion brains are connected forming a huge potential for cooperation, now connecting people who before were not able to participate in developments outside their neighborhood. According to ITU data from 2016, about half the world population has a computer and broadband network connection; and about 94% of the developing world has cellular phone; the world figure is close to a 100% as in the developed world subscriptions outnumber people. The Internet of Things (IoT) extends this number to about 20-30 billion devices connected by 2020 (according to estimates by Gartner and Business Insider). The impact is enormous because highly-connected agents in a network can decide much quicker on future steps than hierarchal organizations ever could. The so-called six degrees of separation, which claims that any two people on Earth are connected via six or fewer links, emphasizes the importance of networks.

The internet not just connects so many people, it allows for new ways of publication, education, communication (groups, social media) and commerce through new business models. This forms the World Wide Web. As an example, a vlogger makes homemade videos with equipment more advanced than movie studios had a few decades ago, he can publish on the web without the approval of a publishing company, at almost zero cost, he could potentially reach 7 billion people and he can make money. In its pure sense internet is user centric, allowing consumers to become producers. The web has a decentralized architecture with open standards and the content and services are distributed. The network supports the emergence of new services and content, at different sizes, at any moment and by anyone connected. Ideas and products can be distributed through a network fast and almost free of cost thanks to de digitization and the dematerialization of products. It empowers creative and productive individuals. Many innovations grow so fast thanks to the reach of internet and the available services of the web, following the same concept of decentralization and open standards. It also empowers the negative and destructive individuals, using the network to rag, fake or undertake illegal activities. The web has become the core concept of our information society both for private and public businesses and information exchange. The tendency of decentralisation could actually be seen in a wider context, like individuals producing energy with solar panels.

Many networks are complex adaptive systems: they evolve and show emergent behavior. Emergent behavior means that non-trivial higher level behavior arises from lower level interactions, with different properties. It usually arises in a self-organized way. Miller and Page (2007) describe the generic properties of social connections as learning behavior of agents and the emergence of cooperation, in reference to Newman (2003). One of the contributions from complexity is the recognition of the importance of non-linearity in the interactions: 'tipping points and critical junctures emerge, where a given system can rapidly change its characteristic behavior' (Miller and Page, 2007, p.216). Also Barabasi and Bonabeau (2003) applied the concepts of complex adaptive systems to the world of networks. They show that the most interesting networks are so-called scale-free networks, which turn out to form the architecture of various complex systems. Mitchell (2009) defines a complex system as a system in which large networks of components with no central control and simple rules of operation give rise to complex collective behavior, sophisticated information processing and adaptation via learning or evolution. It models the behavior of agents, individuals and their interactions. One could differentiate between complex adaptive systems and non-adaptive complex systems, although most complex systems seem to be adaptive. Scale-free networks are connected networks with the property that the distribution of the number of edges per vertex follows a power law, i.e. there are only a few vertices with many connections and many vertices with a few connections; vertices are certainly not randomly connected, see chart 2.4. Such a network evolves with the feature of preferential attachment, which means there is a higher probability of connecting to a vertex that already has more connections than to a random one. Like popular websites that grow ever faster as more links means becoming more popular.

This power law property of scale-free networks could clarify the tipping points in IT networked driven developments. Preferential attachment is likely the mechanism that causes tipping points. Gladwell (2000) describes several examples of empirical tipping points, changes in society that happened spread similarly to an epidemic, like a contagious virus, whereby one or several minor causes resulted in a major effect. It seems these changes were passing thresholds, and were not gradual. It is hard to exactly define the tipping point. Mathematics defines specific 'tipping points' in the context

Chart 2.4 Example of a scale free network



Source: Cockell, S. flickr.com.

of catastrophe theory , which is part of bifurcation theory in the study of dynamical systems. A fold catastrophe function x3+ax contains a bifurcation point at a certain value of parameter 'a' were a stable solution is suddenly lost, which leads to a transition and different behavior, this bifurcation value of 'a' is called the 'tipping point'. In complexity theory tipping points are described as a process. Mitchell (2009, p.253) refers to preferential attachment as the mechanism of 'some process, such as citation, spread of fads, and so on, starts increasing dramatically in a positive-feedback cycle' and, 'alternatively, tipping points can refer to failures in a system that induce an accelerating system wide spread of additional failures'. Miller and Page

(2007, p.144) define ‘tipping’ as the process by which the movement of agents causes cascades of further movement. Tipping points typically cause new structures and hierarchies in a system. The vertices that gain many connections become more important and form a hierarchy in the network. Such a structure makes the overall network more resilient to random loss of a vertex than a random network because most vertices have just a few connections. However, if a few of the most densely connected vertices get lost, the network falls apart. Other examples of scale-free networks are social networks, interbank payment networks and cities.

In sum, the arrival of the information theory leads to digitization of products and a chip industry that managed already for more than five decades to double computer processing power every period at ever lower costs per unit. The distribution of IT products through highly connected networks makes the technological increase exponential. The characteristics of the network show emergent behavior and self-organization, following power laws and leading to tipping points and disruption. The growing importance of the IT technologies in society causes a growing urgency and importance of dealing with unwanted and unforeseen disruptive events.

2.2 Dematerialization, demonetization and its economic consequences

The exponential technologies have far reaching consequences, maybe best characterized by Andreessen (2001, p.1) who summarized the information revolution as ‘software is eating the world’. Software is transforming all kind of products and services into pure digital services and has become ubiquitous in work, finance, manufacturing, healthcare, communication, gaming, toys and education, basically everywhere. Diamandis and Kotler (2012) refer to a chain of technological progression, which leads to enormous upheaval and opportunity, summarized by him as the 6D’s: digitalization, deceptive growth, disruptive growth, dematerialization, demonetization and democratization. They explain that digitalization usually starts small, the new product looks different and is not yet mature. The concept is not taken seriously and ignored, as its growth looks small and it constricts the cash flows and role of incumbent producers. The deception is caused by the initially small growth, with ups and downs and imperfections. Although it grows exponentially, it remains under the radar as long as the numbers are still very small; it is perceived as insignificant and derided, due to linear thinking. And then the disruption comes, all of a sudden for the incumbents, as they don't understand or expect the exponential. It takes a long period of growth to reach 1% market share but 7 further doublings to reach 100%. The two further steps are dematerialization and demonetization. A digitized video camera is no longer a physical product, but an app. Once material goods have been transformed into software, it is dematerialized. Its multiplication and distribution through a network becomes possible, and allows for quick product updates without wasting new materials, and at a much faster speed. In general this drives the marginal production cost down to zero and is therefore called demonetization. At such low cost and with such wide accessibility, the product becomes abundant. Diamandis' sixth D stands for democratization, i.e. the ability for anybody to produce something on the web and distribute it to everybody at near-zero cost. The web in principle offers access to anybody and to all knowledge connected, which allows an individual to be heard. We should keep in mind that one usually needs a commercial platform to reach others and these platforms are far from democratic (see next section).

Just for illustration, the transition described above shows similarities with the enthalpy process of thermodynamics, in which matter moves from solid, to liquid, to gas and to plasma, see chart 2.5a, on the left. Plasma is the ionized form of matter, which does not naturally exist on Earth, though in

Chart 2.5a Enthalpy of a physical system

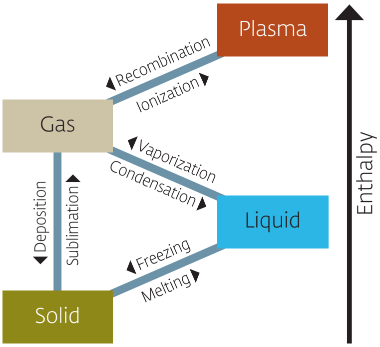
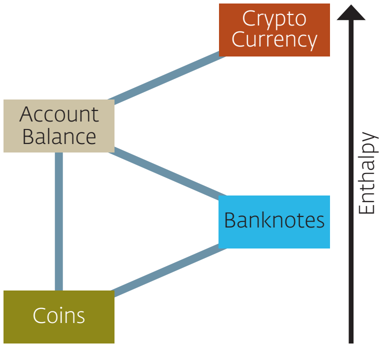


Chart 2.5b Example of 'the enthalpy of money'



Source 2.5a: wikipedia.org.
Source 2.5b: DNB.

the universe it is probably the most abundant form of matter. These stadia could be recognized in the long-term development of several products. As an example the appearance of money, irrespective of the issuer, is mapped onto these four stages shown on the rights side in chart 2.5b. Initially there were shells and coins, these are the solid phase, next the banknotes requiring trust being liquid, than electronic money which is dematerialized, and can be seen as the gas form of money, and finally digital cryptocurrencies which are demonetization money, represented with plasma. Digital cryptocurrencies are coins in the form of software code in a computer network, cryptographically protected against double spending and other abuse, which contains the value as well as the ledger and administration, managed in principle decentralized in the network. Digital cryptocurrencies can be issues by the central bank in the sovereign currency, called central bank digital currency, or issued by third parties in a self-created currency, called virtual money. Today these coins are still expensive to generate because of the energy consumption so one cannot see them yet as demonetized, but the cost is expected to tend to zero due to abundantly available solar energy.

It is important to keep in mind that acceleration of the technology causes disruptions. Once a product/service has been dematerialized, its development leaves the linear process and follows an accelerating growth path made possible by Moore's law and by the network features. The speed and impact could change a whole business sector as the technologies leverage productivity. Originally, businesses needed twice as many people to double the output, a linear process. Then came the machines that significantly leveraged the output for a worker (like using a tractor or a robot in a factory). Still, on this basis, doubling output requires double input (two tractors plus additional worker). With IT, once no tangible materials are involved anymore, the acceleration goes through the roof: the same app can be used by a million users at zero marginal cost (extra users need the investment of a smartphone, but can use it for almost unlimited applications). New companies tend to serve much higher numbers of customers with far fewer employees (typically between ten and a thousand versus over a hundred-thousand), as the cost of scaling is totally different. Existing companies (e.g. telecoms, banks) have no choice but to transform, and shed large amounts of old-fashioned jobs while new jobs are created at other places in the same sector.

In the context of this paper these development are relevant because this technology is about to change a number of systems into complex behavior with the dynamics and disruption that are hard for people to imagine and predict. The economic effects of dematerialization and demonetization are further discussed in this section.

The dematerialization of products could significantly change the business process and impact a whole sector. Dematerialization of a product significantly diminishes the costs of material as well as physical transportation, distribution and sales basically disappear, with remaining cost in development, energy and security. For instance, the dematerialization of bonds and shares cut the time lapse and cost of trade, resulting in full automation, and has made algorithmic trading possible. The impact on post-trade is even higher as the handling and moving of titles can all be done electronically. The network connectedness further improves the efficiency of production, distribution, information processing and customer interaction. Also the potential change of a whole industry could have an important impact: wiping out intermediaries, with competitors needing to cut their high cost levels or completely change their business. Postal services had to change their business to distributions of parcels as competing with free email is impossible. At dramatically lower cost than the product it replaces, the marginal cost moves to zero and the product becomes abundant. Therefore, different business models are used, often based on advertising and reselling personal data as source of income. Yet the threat of scarcity still dominates our worldview. Few resources are truly scarce, most are mainly inaccessible. Scarcity usually means value, but new companies take something scarce and they make it accessible and abundant.

More and more products get dematerialized. An increasing amount of equipment we used to carry around have become an IT application.
As mentioned before, Kurzweil (2005) found that once a technology shifts to an information-based environment, the pace of development jumps onto an exponential growth path. Kurzweil, together with Diamandis and Kotler (2012) and Ismail et al. (2014) identify the following areas of technological developments heading for (partial) dematerialization and abundance:

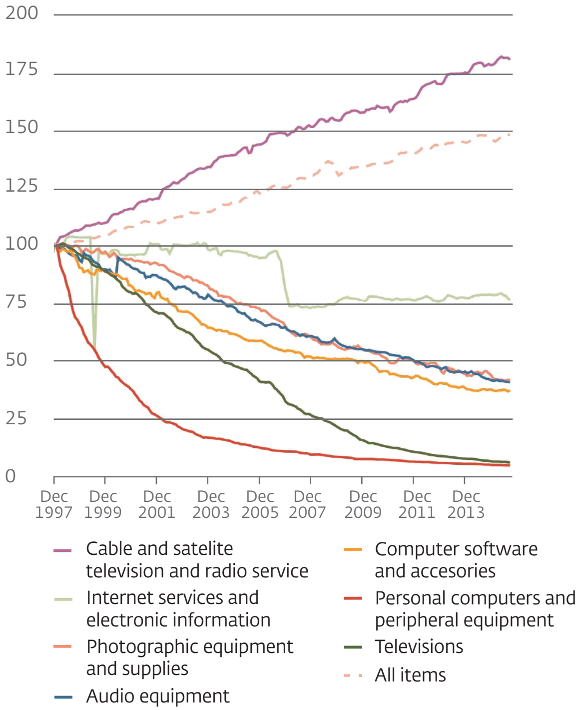
- Transportation: e.g. driverless cars, drones, 3-D printing avoids transportation;
- Food: vertical farming and cultured meat;
- Energy: near-zero solar panel costs;
- Healthcare: clean water globally (with abundant energy), medical apps, individualized medicines;
- Nanotechnology, synthetic biology: repairing body parts;
- Education: internet learning (MOOC's, Khan Academy, YouTube);
- Entertainment: games, movies;
- Banking: basic account services, virtual currencies;
- Artificial intelligence, blockchain and robotics: horizontal technologies, impacting all areas;
- Time: would abundance lead to human boredom, how do you occupy yourself?

What is the economic relevance of abundance? The trend may still look small, but the technology grows exponentially so we need to be careful not to forget that such developments may look insignificant for a while, until the tipping point after which it overwhelms us. A few examples: with MOOC's the cost of education drops for repetitive use, as well as travelling cost and time; and one could reach exponentially more students from anywhere. The high density and distribution of smartphones allows for leveraging the power of the crowd as one can collect data from the sensors of many individuals' smartphones and use all this data to compose a new data service. Take traffic services, estimating the number of people at festivals or demonstrations, search for a missing person, composing a mega movie compiled of crowdsource photos of a specific event. The point is, it is fast, dynamic and much cheaper as it leverages the installed base and it leads to a more robust product as one rarely had access to such a good sensor network before. Another example, when driverless cars become ubiquitous, the total number of cars could decrease to a fraction of the present number because you call a car only when you need one; the cost of individual transport would come down significantly (ultimately the poorest people on earth will be chauffeured around). The consequence would be as wide as changing cities (parking, roads), disrupting driving schools, taxi companies and car insurers. In a way similar to what happened with music stores and other retailers. A last example of an exponential technology that has a much wider impact than initially assumed is blockchain. It is the smart data structure used in Bitcoin but in the meantime people experiment with blockchain in all sorts of applications that require identity check, non-repudiation and full protection of integrity of data. Besides its potential to change money, these features are valuable to improve and further automate asset management, accounting, audit, supervision, national registries, automation of simple lawsuits and protecting the safety of our food by registering all ingredients. Some see blockchain as a new technological paradigm because of its broad potential.

To continue on the economic relevance, the impact of dematerialization and related demonetization is pressure on prices. A smartphone today is apart from a telephone, also a computer, a photo camera, a videorecorder and player, a music player, a GPS, a voice-recorder, a pager, a digital watch, an alarm clock, an agenda, a remote control, a game console, a videoconferencing system, etc. Most of these products you do not need to buy separately anymore. Diamandis (p.289) illustrates this with today's smartphone containing products worth 900,000 USD compared to the cost of these products in the eighties. One can argue that most people did not have all these products at that time, but many did have a few at least, bought at higher prices than people spend today on the smartphone. Chart 2.6 illustrates the significant price decrease of consumer electronics. Over the years, in the western world, an ever smaller part of income is spent on the basic needs in life, like food, and more money is spend on services and

Chart 2.6 Consumer price indexes of some electronic equipment

Consumer price indexes for televisions, computers, software, and related items, not seasonally adjusted, December 1997–August 2015 (December 1997 = 100).



Source: US Bureau of Labor Statistics.

information processing products; the information age is likely to drive this further, globally (for instance in the US between 1960 and 2007 the share of disposable income spent on total food by Americans, on average, fell from 17.5 to 9.6 percent, see www.ers.usda.gov). The propagation of exponential technologies is likely to continue and to accelerate with a continuing downward impact on prices.

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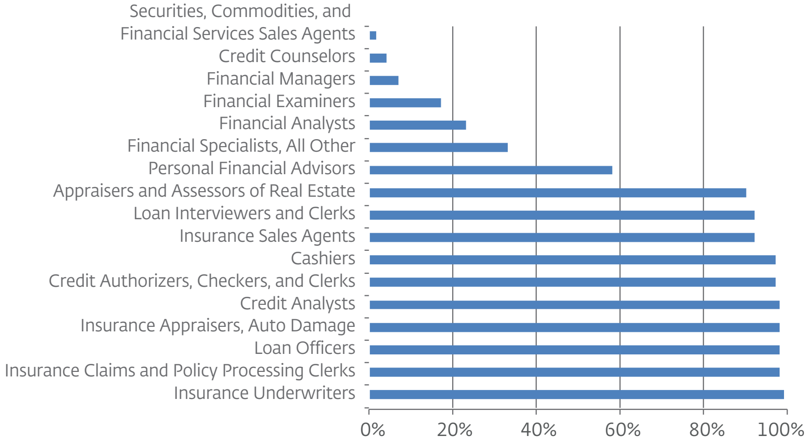
On the other hand, new technologies also require vast (initial) investments, sometimes accelerated by government policies. For example, an increase in usage of electric energy leads to investments in electric cars, charging stations, in electric power production facilities (solar panels, windmills, hydroelectric power) and could lead to disinvestments in other production facilities like coal power stations and result in a firm decrease of oil demand. The faster the usage and market grows, the faster the product could run towards abundance.

Further pressure on prices could result from some services (news, communication) being 'paid' for through providing personal data and by watching ads. The importance of this business model increases with more products moving from tangible to software. This trend could diminish the role of money in the real economy and in the longer term information might replace money as the main mode of discourse in society. A further expenditure-reducing force, and sign of prosperity and wellbeing, is that better cooperation through social networks and platforms facilitates a sharing economy and helps to reduce waste of materials and energy. A sharing economy basically unlocks idle capacity which allows for an enormous efficiency gain.

Economic relevance is also seen in the impact on jobs and skills required. Computers are performing increasingly more complicated tasks which will cause many white collar jobs to disappear. A shift that has already been taking place for a long time, since the advent of computers and before through the transition of jobs from agriculture to manufacturing, but the exponential growth characteristic of information technology could lead to a much faster shift this time. Several technology companies showed they only need a small fraction of employees to deliver similar services to their competitors before. Obviously affected sectors will show job growth for designing and building

Chart 2.7 The Future of Employment, Finance related jobs to be automated



Source: Frey and Osborne, Oxford University.

the algorithms, but in the longer run also part of the programming jobs will be carried out by machines through artificial intelligence. The tendency is that people could focus more on the creative tasks, new ideas and new solutions. The structural changes also demand education to adapt radically and teach children the right skills and stop educating them for jobs that are about to disappear. In an extensive analysis, McKinsey (2017) estimated the impact that technologies available today could have on our jobs: about 45% of activities people are paid to do today, could be automated in the next few decades, and one third of the tasks of 60% of all jobs would be automated. They signal that the technical potential for automation differs dramatically across sectors and activities, and they warn of the uncertainty of the timing, depending on new technology adoption. Frey and Osborne (2013) analyzed how susceptible jobs are to computerization and estimated the probability

42 of computerization for more than 700 occupations; chart 2.7 shows jobs from this analysis related to finance. Diamandis and Kotler (2012) foresee a fundamental decrease in the number of total jobs and thus difficulties in obtaining income. They argue that a universal basic income will therefore be necessary, and assume a limited level would suffice based on the premise that exponential technologies will continue to rapidly demonetize our costs of living. Jobs will certainly change, and new jobs will appear like we have seen before, however it is uncertain how fast people could adapt if the forthcoming automation accelerates rapidly.

The impact of exponential technologies on existing companies is likely to be disruptive. Ismail et al. (2014) show the average lifespan of a company listed in the S&P 500 has significantly decreased from 67 years in 1920 to 15 years today. They urge companies to swiftly become an 'exponential organization': a non-linear, scalable organization, not owning assets or workforces but leveraging external resources to achieve their objectives. Exponential organizations manage abundance, build their business on new sources of information or convert previously analog environments into information; they will use data dynamically and find new information in big data. Exponential organizations use scalability of those aspects of the company's product that is information-enabled, as information is essentially liquid major business functions can be transferred outside the organization, to users, fans, partners or the general public. Typically, small companies are beating big ones, e.g. Airbnb versus hotel chains, and WhatsApp versus SMS, leading to more disruption of products, companies and markets. Incumbents have no choice other to change their business and become receptive to new ideas, to experiments and the risk of exponential technologies. To quote Abraham Lincoln: 'The best way to predict your future is to create it'.

In practice however this is not easy. Large and older companies have a tendency to focus on managing existing products and cash-flows, and to become risk averse. Christensen (1997) shows that innovation rarely comes from the status quo, the success of the start-up is to offer a less expensive product using emerging technologies and meeting a future or unmet customer need or niche. Hagel and Brown (2010) clarify that 'scalable efficiency' is the paradigm that drives most corporate strategy and corporate architectures. Scale - linear scale - is the raison d'être of the linear organization, and they conclude that 'our organizations are set up to withstand change from the outside, rather than to embrace those changes even when they are useful' (Ismail, p.41). The lifecycle of products (and companies) could be seen as S-curves and the disruption is when you move from one S-curve to a next one. Christensen wonders why such jumps from one S-curve to another is a stumbling point for existing companies. He finds that the question of whether a technology is disruptive depends less on how radical a technological advance it is but more on its specific effect on the S-curve. If a technology pushes performance up an existing S-curve, it preserves the power of the incumbent. When a technology requires a new S-curve, particularly when it starts at a worse price-performance point than the current technology, the newer technology tends to be disruptive and to change the industry structure. He says the innovator's dilemma is the tough decision by an executive who cannot justify investing in a technology that, at least initially, has a worse price performance, but may be preferential in future. Big companies risk their board not seeing the future importance of a new development and ideas perceived as less important do not get the resources. Usually resources go to promising technologies to continue near future cash flow.

A known example of the disruption of a large company that missed the move to a new technologies is Kodak. It had invented the digital camera, had the patent and the opportunity to be the first and leading digital camera producer.

But Kodak saw this new technology as a threat to its current earnings from films and related business, ignored the technology and its implications and went bankrupt, disrupted by the technology (that they had invented). Another example is Blockbuster that was disrupted by Netflix, a company that dematerialized and demonetized the video industry, although Blockbuster seemed to have invented this business. In a similar way, banks may risk their profitable business to new software solutions for lending and payments. Even though regulation protects the industry, the fight between Uber and the taxi industry may lead as an example.

In summary, exponential technologies allow products to dematerialize and to distribute them through the network. The feature of software to create multiple copies at near-zero cost causes demonetization of the product and the spread through the network makes the product ultimately abundant. This likely causes lower expenditure and lower prices. This model allows for start-ups to grow fast, and shakes up existing companies and jobs in a disruptive way.

2.3 Further consequences to society

This section looks at the wider impact of exponential technologies and the disruptive changes they cause in society. It looks at the platforms, the used model, the data, trust and dominance. Next it looks at the value of data and how the global force of the expanding technology put pressure on our institutions.

In the previous section Diamandis' (2012) sixth D for democratization was mentioned. He refers to individuals who can launch their ideas and products on the web with great reach, which was almost impossible to do with tangible goods and also because distribution required approval from a reseller. Individuals and small teams can create multibillion firms that change the sector completely, such as Google, Facebook, WhatsApp, Airbnb, Uber, Wikipedia, etc. Referring to the aforementioned example of the vlogger, a child can now be a producer and reach a million followers, which would have been impossible a while ago when the video camera, access to production and publication and the distribution channel itself were too expensive or inaccessible. The same holds for publishing your ideas, books or music. Local community initiatives are another example of the democratization opportunity that exponential technologies offer. Neighborhood surveillance, local energy production, car sharing, co-working, there are multiple examples of sharing economy initiatives that emerged from the technology possibilities. Along the same lines, private cryptocurrencies would be an example of the demonetization and democratization of money, as the issuance starts with some individuals mining the coins instead of issued by a central bank, and transactions could be performed at very low marginal cost.

In practice one is not really independent as you usually need a platform to be noticed and reached. These platforms are usually dominant players that use a 'winner takes all' model. With large sums of capital they buy market share, push the new idea, create a world brand, maximize their network externalities and become a new, global, monopoly. The search engine decides what you will find, which depends on commercial interests and what others like, the retail platform decides your choices and what you should buy, and the social network platform commercializes customer data and locks you in leaving not much room for competition. The individual needs the reach and visibility of these players, or otherwise stays unnoticed. A few examples: the vlogger depends on Google/YouTube to be found and watched; Bitcoin mining now requires large investments impossible for the average individual to afford; and internet reviews tend to turn from a democratic voice into a commercialized recommendation.

This ‘winner takes all’ concept from the platforms looks similar to the rich-get-richer theme, newly discussed after Piketty (2014) published his observation of an increase of wealth and income inequality in many countries. Would dominance of the large technology firms worsen inequality, or is the force of democratization due to technologically-driven abundance pushing this back? Piketty warns of a return of the 19th century situations when the rich got richer and their next generation doesn’t need to work, causing social and economic instability and posing a risk to democracy. He claims this is caused by return on capital being higher than the rate of economic growth and he predicts it will continue in the coming decades. Since the First World War, economic growth was outperforming capital returns, which according to him reduced income inequality. This causal relationship is questioned by Góes (2016) who shows data that proves the opposite: a decrease of income inequality in at least 75% of 19 developed countries where the return on capital was indeed higher than economic growth. To what extent Piketty’s hypothesis holds for the emerging technological developments, remains to be seen. Platforms may cause a risk to social and economic stability because of their dominant influence of knowledge and information of citizens they possess. On the other hand, democracy and stability could gain as they facilitate communication and people reaching out, which brings low cost opportunities to those who didn’t have access to telecommunication, education, banking and the like. Many technology companies manage to gain access to large sums of money to launch their ideas and quickly build up market share. A relatively small group of very rich provide capital to start-ups, and here indeed the rich do get richer. However these are entrepreneurial activities, those rich people take risk, and surely many technological ideas do not become successful at all. Here it is not money spent to retire, rather the opposite. As explained earlier, abundance could push down the economic growth numbers. Low growth rate is part of the issue identified by Piketty but these lower growth numbers are caused by abundance actually increasing welfare due to less material use and less waste to the population.

More worrisome seems the dominance (hopefully not the 7th D) of the platforms and the competitiveness of the market. The commercialization of the network and the data provide so much power that alternative providers have little opportunity to compete, leaving the consumer with little choice further which reinforces the 'winner takes all' model. The competitive landscape has changed in many sectors by companies that, unexpectedly, shook up various markets with their new business model. As they use the network capabilities to the maximum and customers like the new possibilities they deliver, the network facilitates these companies to reach strong customer lock-in and they become a winner. The more people are interconnected and the more goods and services become software and get onto the network, the more we will see such complex behavior and non-linear developments. Which causes uncertainty in society. Andreessen (2001) said information accelerates every industry, at every level, software is automating and accelerating the world, hardware is the new software.

As an answer to the growing uncertainty, Hagel and Brown (2008, 2010) describe the idea behind the emergence of platforms explained with the push-model and a pull-model. With the push-model people are passive consumers and, as business is rather resource centric, demand can be anticipated and control is centralized. Whereas with the pull-model people actively mobilize the appropriate resources when they need it. People can immediately get together, innovate and use the distributed resources to exploit the opportunities the platform provides. Pull fits the uncertain demand which cannot be anticipated, is built around people rather than resources, typically allows for the lean rapid incremental innovation and can bring positive sum results. The strategy used is to scale the company executing a successful idea towards a platform: the increasing scale allows connecting more services to the same customer base, attracts new customers and lowers the chance they will leave as the platform services become an ever greater part of their lives.

48 These customers generate a tremendous amount of data. It seems that the last two years have seen ten times more data created than in the entire history of humanity. The ones in control of the data have the power, they can monitor people's behavior, in order to give better services as well as provide tailor-made commercial offerings. The platform also empowers its users further through the network effect. The result is an ever stronger customer lock-in. So the business model differs from the companies that grow to scale and save cost.

The platform companies collect lots of data from individuals and companies which leads to convenient and low-cost services, but also to being influenced and restricted in freedom. People voluntarily upload lots of personal data, some of which is privacy-sensitive, to be able to use the so-called free service the platform offers. Information ownership has changed, often unconsciously. Apart from great services and opportunities social networks offer, they also create uncertainty and group pressure, and lead to exponentially growing amount of messages and time spent with such services. Consequently, the platform companies know so much about people, they can play the role of trustee and build trust based services. They create trust between strangers, connect them, offer reviews and recommendations. Some services depend totally on the reviews through the network: without a good reputation (good car driver, decent home renter) it is almost impossible to continue offering your service via such platforms. This could improve the quality of service in the sector and puts pressure on incumbent producers (taxis, hotels, banks). Companies that manipulate the review process show they do not understand the mechanism of trust and fall into the trap of a short-term gain and long-term loss.

We tend to underestimate the impact of new applications and the value of data. Through providing their data, individuals risk their freedom and become influenced unconsciously. Many exponential technology applications are presented as a social activity of sharing data for a common service, which stimulates the growth of the company and the value added for the customers. But people forget that data provided by the user is filtered, commercially applied, and data sent to the user is also filtered based on user preferences and commercial reasons. As a consequence, people are influenced in their choices as they receive offers and news that has been selected based on such filters, either set by the companies or by the individuals themselves. As a consequence, it lowers critical thinking as people get further confirmed in their biases and less confronted with diverging views. The increased spread of data seems to harm individual's privacy and freedom. Governments could also abuse modern technology to limits citizens' political freedom and self-government (like Snowden's revelations, increased possibilities of widespread surveillance). The rapidly changed use of data by companies and governments creates uncertainty and major shifts in ownership and dominance.

New technologies have the potential to destabilize many of our institutions, such as peer groups, mass media, data ownership, money, the nation state, formal registries, etc. Some become automated rigorously, for others their relevance may change, or the relevant actors may change resulting in a shift of power, and some could well be replaced by new structures and institution. New technologies bring up discussions on ethics and regulation, e.g. on access to DNA, on neighborhood nuisance from Airbnb, and on ethics of unmanned aircraft used for warfare. Government institutions feel forced to quickly understand and react adequately to the risks and opportunities of new technology, its collected data, its applications and the risks they bring to human rights. Particularly in healthcare, the fast developments require a much quicker reaction from relevant authorities, on issues like integrity, ethics of replacement of body parts and medicines. Developments in drugs go so fast that some are already out of date once the regulatory approval for market introduction arrives. The technology opens up big issues that require a swift response. Clear limits need to be set to protect ethical values, safety and civil rights, think about the integrity of the body, ownership of data, etc. Within such limits, innovation can flourish to bring us new and improved services, and new business models to overcome inefficiencies that we are unaware of. Regulation should be adapted quickly when new technology shows it is limiting us unnecessarily, each time striking a balance between not killing the innovation's power for improvement and continuing the protection of our health, safety, privacy, etc. One can question the effectiveness of the intellectual property protection model for society, as it turns out to be counter-productive for solving a number of existential problems we have in healthcare, food and solving pollution. The effectiveness of patents is under pressure. More money is spent on litigations than on new patents and the required timelines and cost for patents seem no longer productive to companies like Toyota and Tesla, that opened up patents because they believe their companies will grow faster through open competition and de-facto standard setting instead of a business model based on royalties. Open source innovation facilitates cooperation and growth for new and better solutions like Linux and Android have shown.

New technologies have a global impact due to interconnectedness of networks. The technology is not bound, the reach of the internet allows technology to be used anywhere in the world and access and usage have become available and affordable globally, as shown in the beginning of this chapter. In terms of trade, countries heavily leaning on labor-intensive sectors for production and trade will be hurt the most. For instance, production of (plastic) goods could shift to local 3D printing, produced right at the location where it is needed. Biotechnology allows for meat production to be replaced by local protein growth at vertical farms, even right in cities close to consumers. Such examples of local production could affect the end-product distribution function of major harbors, although raw materials still need to be shipped. For dematerialized products, the distribution moves onto the data network. Call centers could be replaced by automatic voice systems. Following the same logic of how disruption works, Ismail et al. (2014) foresee an important effect on nation states, expecting city states and small countries more likely to adapt sufficiently fast than large countries because they can afford being less risk averse and often have faster decision-making due to the smaller size. On the other hand, challenges like rights and limits of AI, ownership of data, DNA manipulation and power of global companies are global, and suggest the need for global structures to meet them. The world organization of nation states with national politics seems no longer consistent with the global problems mankind is facing.

Maybe our intelligence is no longer in sync with our consciousness, feeding the fear of some that our self-created AI will ultimately rule us like super-humans, and we will end up jobless and bored. Biesboer and Van Est (2016) touch on the fear people have that we lose our uniqueness to new technologies. The human power to think makes us (feel) superior among animals but our development of AI creates machines that can think which undermines our unique feature. Van Est signals our struggle to cope with the emergence of new applications and technologies. Transitions and also the speed at which they arrive seem to be hard to understand for people. The institutions from which we expect structure and protection, have difficulties in quickly adapting to what new technology makes possible, while some companies take advantage of this lack of speed. He diagnoses that we do not fully understand the social and economic value of data. When in a country natural resources such as natural gas and oil are found, usually the government ensures the country as a whole will benefit from the resource. Either by setting up a government-controlled extracting company, or be setting up an agreement with the private sector to extract the resource but handing over the proceeds to the government. He suggest a similar deal could have been made with Google for its Streetview: to remain owner of the data and to retain the control over who and how that data is exploited.

Finally, how fast will exponential technologies change our lives and structures? Kurzweil (2005) expect it to happen at the same speed as Moore's Law and predict it runs towards a point of singularity and beyond. Singularity being the point where technology created by ourselves has become as smart as ourselves and will outpace us as it can continue Moore's doublings because of this intelligence (chess and Go were just a minor preview). He expects one will be able to buy a computer with human brain capacity for USD 100 in 2020, and expects man to be able to build computers with intelligence indistinguishable from that of humans by the end of the 2020s (passing the Turing test) and that most diseases could be eradicated as nano-bots become smarter than current medical technology. He expects humans to become non-biological after 2030 (redesign organs), exist in virtual reality, upload their brains, followed by multiplying and linking all human intelligence wirelessly from our neocortex to a synthetic neocortex in the cloud, leading ultimately to the onset of the singularity by 2045, when humans will be dematerialized, opening up the way for space travelling at the speed of light or even teleportation by using entanglement. From another point of view, Kelly (2010) sees the evolutionary forces driving technological development, and he questions whether we are able to manage the increasing complexity at all. He argues that we do not have much control over the long version of Moore's Law; even if we wished to stop it we cannot anymore. Consequently the technological acceleration defines the speed of change; which would support Kurzweil's futuristic view. Kelly (2010, p.197) states 'Technology chips away at our human dignity, calling into question our role in the world and our own nature. This can make us crazy. The technium is a global force beyond human control that appears to have no boundaries'. Others believe humans will not embrace these changes so eagerly, will step on the brake and set rules to protect the status quo of organizations, jobs and power. However we saw national regulation does not fit global technological development, so that seems hard to organize globally. We have seen that innovation builds on innovation and centrally controlling such a process seems hardly feasible.

In summary, we saw the wide impact of exponential technologies on society, how business models change and allow start-ups to emerge and quickly become a dominant platform, providing global access to services and great innovation and disrupting old structures. Institutions are usually late in their reaction to this new dominance, which has global impact. The exponential technologies could potentially change and disrupt any sector, and the certainty and control we think we have, is transformed in a more disruptive and uncertain world.

2.4 Consequences of exponential technologies in the financial sector

For illustration purposes, this section provides a brief overview of the challenges that exponential technologies bring to the various actors in the financial sector. This section lists the lines of change of four main technology consequences: dematerialization, abundance, technology for body repair and new players in the financial market.

Dematerialization

Dematerialization both effects bank services and the organization of a bank. The dematerialization stands for strong cost reduction and allows real-time processing. For instance in the last decades the securities industry has changed significantly due to the dematerialization of asset titles and it will continue to increase efficiency, probably towards real-time post trade handling. Algorithms have been introduced for optimization of liquidity in payments, for trading (high frequency trading counts for 70% of market volume), customer banking service have moved from paper based and branch office counter located services, towards desktop computers and smartphone apps. This trend

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continues: payments are moving towards real-time, AI algorithms will support close to real-time lending and investing services, help insurance companies in processing claims and reduce cost and pressurize the financial advisory sector. Often the consequence of algorithms is increased vulnerability to sudden events: high frequency trading has shown several out-of-control jumps in the market place.

Banks and insurers become real-time information processors, in a similar way to what happened with telecom providers and retailers, ultimately operating with just a small fraction of employees skilled in organizing new business and developing algorithms. Banks and insurers have to move, otherwise they will be disintermediated by new players who could start-off as a small IT company without the heavy costs of the existing organization.

The dematerialization facilitates access to banking services. Banking has become available in countries where only recently the majority was still unbanked, via services such as M-Pesa, supported by the abundant availability of telecommunications.

The dematerialization of money has been touched upon before with the enthalpy diagram. Apart from the effect of fewer notes and coins the most interesting phase is the demonetization of money in the form of virtual currencies with potentially large effects. Such currencies could be issued by central banks and by private parties. When issued by the central bank the digital coin is an alternative appearance of the sovereign currency and could be issued to the commercial banks replacing the electronic currency, but it could also be issued directly to citizens without the banks which would have a firm impact on the present financial system; it would allow citizens to exchange central bank money directly person to person without a commercial bank in between, similar to coins and notes today. When issued by private parties a virtual currency has its own value and forms an alternative money circuit. Such a coin is initiated by a private party and issued by a network that decentrally manages the coin, like Bitcoin. A virtual coin could also be issued by a commercial bank, a retailer, but also by a city. Via exchange platforms people can buy and sell the virtual currency through paying with other, public, currency. People manage their virtual currencies with e-wallet software in the form of an app on the smartphone, and this way they can also initiate transactions to others, or to retailers.

Private virtual currencies require no banks in the chain nor central banks, as trust is in the cryptographic protocol of the underlying virtual coin software. Some see this as the main benefit that the virtual currency is not managed by the present banking system. Many initiatives for local virtual currencies have been launched, some directly intended to support local trade and contacts as the banking system in crisis failed to serve these local needs. It proved to strengthen the social role of money as a means to connect people. Other benefits are lower transaction cost, in particular for cross-currency, and convenience of immediate payments with global reach. The trustworthiness of the unknown parties, platforms and software used, could be seen as a benefit or drawback, depending how much trust you put in the software and the issuing process. Drawbacks of virtual currencies are the fluctuating value and the limited acceptance of coins. These coins work as medium of exchange, but not (yet) as a unit of measure and store of value; they are mainly speculative.

Abundance (intangible and at near-zero costs)

The trend towards abundance of products and service would lower the volume and total amount of loans. Much lower levels of car loans are necessary when ‘apping a car service when needed’ becomes normal.

Lower mortgages are expected when robots and 3D-printing fulfill the promise to significantly reduce building cost. As a consequence prices of existing houses will fall, pushing existing mortgages under water and pressurizing the securitization of mortgage loans. The non-life insurance business could also be affected by abundance, as claims received decrease when more goods becoming intangible and costs down to zero. However, at the same time the value of data increases and need for protection and insurance increases.

Abundance will have an effect on the inflation targets for monetary policy. As shown earlier, the firm price-pushing effect caused by abundance may lead to a structural lower inflation level, without a demand problem. It actually represents significant economic progress, globally, while hardly visible in classic GDP measuring. Local production could lower trade and distribution volumes, typically affecting trading countries. The sharing economy, supported by networked technology, may further push down growth in terms of GDP as it unlocks idle capacity and allows for substantial efficiency gains.

Technology for body repair

Exponential technologies applied in biology, nanotechnology and medicines lead to detailed knowledge of the working of the body and allow for the possibilities of precision repairs in case of diseases. With algorithms, individuals gain more probabilistic knowledge of their health and risk to diseases, which they could use to game the (life) insurance company. Advanced medical apps, like IBM's Watson, provide (probabilistic) insights in people's life expectancies impacting health insurance and pension plans. Better informed people could make smarter selections to insure, which puts the social component of insurance and pension under pressure. Advances in medical IT and nanotech applications support more sophisticated and precise curing, including personalized drugs, and the knowledge will help us to focus more on prevention. This is expected to lower the cost of healthcare, and increase our life expectancy to levels that have firm and immediate consequences for retirement plans and the pension funds. Less paid work and longer living would make pensions unaffordable, which could only be mitigated by much lower cost of living thanks to abundance.

New players in the financial market

New players change the banking service landscape. A disruption of existing business models is foreseen, with the large impact on existing players (see above). They know this and are already adapting their business to an IT and experimental culture. New platform firms arrive, in niches but eager to apply the 'winner-takes-all' model. Lending platforms for businesses and to consumers may profit from platform and network dynamics providing peer-to-peer lending and crowdsourcing. The new players will pick the services with the highest margins and services that best fit a social need. The bigger impact may come from the communication platforms (such as WhatsApp, WeChat, Google, Microsoft and Apple) to provide payment services as side business to their messaging services. They could further commercialize on the data and customer profiles they already have, for instance through lending services. These platforms could work with much lower running costs after platform initial investment, and offer creditworthiness checks in seconds rather than days. The interest of such new global players in the payment market may collide with the national regulator's approach to safeguarding smooth functioning of payments. The mass payments processing business is typically scale business and already organized efficiently, there is most is to gain with the costly remittance services.

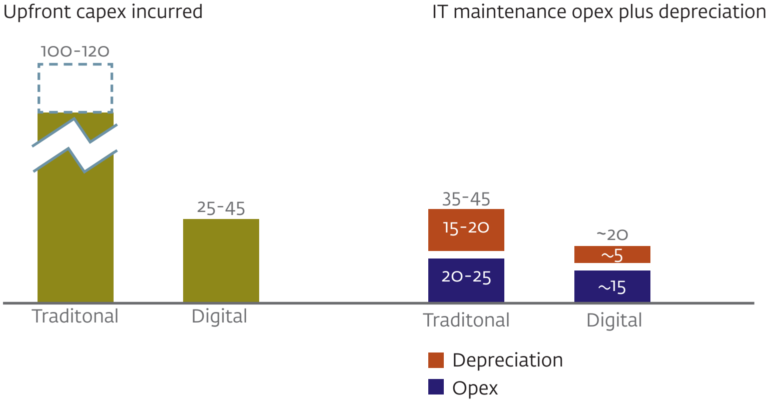
The demonetization of money allows new players to issue money, as we have seen with Bitcoin and other private cryptocurrencies. In principle, cryptocurrencies could be issued by anyone. The trust in money usually provided by central banks is with Bitcoin and the like replaced by trust in the blockchain architecture, the strong cryptography and the consensus protocol requiring enough sites to validate each payment and avoid double spending. The trust is offered by design between people who do not know and trust each other. Speed and energy consumption are still issues, but these may be resolved in time (abundant solar energy at near-zero cost). These coins threaten the monetary policy task of central banks as the (local) alternative currencies cannibalize the sovereign currency and complicate their task to safeguard the smooth functioning of payments. Of course the same technology could also be used by central banks to issue a digital coin in the sovereign currency. The blockchain technology is likely to have a much wider impact than just money, as many processes could profit from a fully automated check of identity and historic transactions applicable to any kind of registry; and it would make clerical work redundant.

New players with their new business models will require access to the financial market from the regulator. This puts a challenge to the regulator. The requirements for a license should protect the claims of the consumers, should not limit the technology or model used as long as it protects the consumer's interest and should protect the financial stability. Regulators may get confronted with emerging self-appointed banking platforms that operate potentially worldwide, from another country, based on quickly created trustee relationships with and between its users (cf. Airbnb, Uber). Authorities need to get prepared for overseeing companies that will be very different from the present ones. The new technology also offers opportunities for authorities to amplify or ease their tasks. Think about the transparency that could be gained from modern data techniques and AI algorithms that monitors money flows. Real-time settlement of securities could lower liquidity and collateral risks in today's post-trade chain significantly. To what extent emerging start-ups can grow and provide services depends in the financial sector much on national regulation, the legislator's willingness to allow such players in the marketplace and to the extent they get access to the existing infrastructures. However IT companies work globally and could build firm pressure on existing markets thanks to the backing of major investors to acquire market share. Uber has shown it can put pressure on existing market regulation.

Banks of course have already incorporated digital technologies but the digital revolution in banking has just started. Many end-to-end bank processes, such as financial transactions, opening an account or getting a car loan, can be fully automated turning the whole bank into a digital bank. McKinsey (2016) expects that a newly built all-digital bank requires substantially lower capital expenditure and lower operational expenditure per customer than for traditional banks, see chart 2.8. They foresee such a digital bank needs a two-

Chart 2.8 Build a new all-digital bank at substantially lower capital expenditure (capex) and lower operational expenditure (opex) per customer than for traditional banks

IT costs, USD million



Source: McKinsey (2016).

speed operational model, a traditional stable transaction back-end system and a flexible front-end system with short release cycles.

2.5 Conclusions

The propagation of software through our society transforms linear business into exponentially growing new business. The rapid development of new technologies causes dynamics in a world deemed to be stable world. Information theory led to digitization and a whole industry has grown to continuously improve computer processing power at ever lower costs per unit. Technology using the IT and its acceleration grows even faster once used in highly connected networks, which makes it an exponential technology. The characteristics of the network support self-organization of entities from which new phenomena can emerge, and developments in networks show power laws, tipping points and disruption. Exponential technologies allow products to dematerialize and distribute them through the network.

The feature of software to create multiple copies at near-zero cost causes demonetization of the product and the spread through the network makes the product ultimately abundant. It brings us great innovation, new services and low cost access to reshaped products. This likely also causes lower expenditure by individuals and downward pressure on prices. Start-ups and major IT companies use the possibilities of the all-digital services to grow rapidly, cut inefficiencies and consequently shake up sectors and disrupt companies and quickly automate jobs. As an illustration this chapter has shown the potential impact of exponential technologies on the financial sector.

Exponential technologies are applied via a different business model, a ‘winner-takes-all’ model, allowing for start-ups to emerge and develop quickly, providing global access and becoming a dominant platform disrupting the old structures. Institutions have to handle the emergence of new applications and the dynamics it causes but have a hard time catching up and dealing with the global scale. Although the network in principle democratizes in the sense they allow each individual to publish ideas and distribute any digital form of product, you usually need a platform to have reach and be found, which makes the individual dependent of a large commercial platform.

Exponential technologies potentially disrupt any sector and the certainty we think we have. Great benefits are expected in health care, energy and decreasing pollution, in addition to all kinds of convenience services. Development runs in a more dynamic and emergent way, with unexpected events, away from equilibria rather at the edge of chaos. This behavior is complex and does not fit reductionism and traditional modelling. We need tools and models to deal with the complex environment as exponential technologies seem to make the world behaving more complex. The rapid developments at an ever wider scale make the need to prepare for and handle disruptive events more urgent and important.

3 Various explanations of our ignorance of disruptive events

We saw that network-based information technology may cause more complex and non-linear dynamics in society leading to more unexpected, disruptive events. This chapter reflects on a variety of possible explanations found to clarify people's difficulties and ignorance of disruptive events. It starts with the brain to reflect on how we think, followed by descriptions on how we deal with time and probabilities. These form a base to focus further on risk, risk models as well as on uncertainty as clarifying avenues of our ignorance of disruptive events. In the last sections the focus is on limitations of mainstream economic models, on complexity economics that actually recognizes disruptive behavior and on the role of education in preparing us for non-linearities in life. This chapter ends with concluding remarks.

3.1 Possible explanations based on our brain functioning

People tend to think in an imprecise manner, we actually make up stories. Kahneman (2011) explains that most of our thinking is fast, instinctive and emotional, taking place in the part of our brain what he calls 'system 1'. Our more deliberate and logical thinking takes place in our 'system 2' which is rather slow compared to system 1. It seems that most of the time we use our system 1. He shows when confronted with a difficult question, our system 1 seems to translate the difficult question into a different, more accessible, question that we can answer fast using heuristics. Heuristics are a strategy to simplify the world and a way to making things more efficient, saving energy and processing capacity of the brain. Heuristics are also called rules of thumb. You often gain speed at the cost of accuracy. What makes it challenging though, is that our system 1 cannot be turned off at will. Moreover, our system 1 is bad at causality and relates events of luck or bad luck as if they were related, often unjustifiably. Taleb (2010) calls this the narrative fallacy: the stories we tell ourselves to make sense of the situation. As a consequence we rewrite our own history. Both Kahneman and Taleb show our overwhelming tendency to see patterns in randomness. Human pattern recognition is a very fast and strong feature and necessary for survival. However, the drawback is that if there is no pattern our brain still makes one, which clarifies why we often see non-existing causality in unrelated events. Our need for causalities disturbs us in distinguishing facts from stories.

System 1 works easily with similarity, but has a hard time with probability. Only our system 2 can understand statistics and requires good concentration and a well-rested brain. Kahneman explains system 2 should correct and control system 1, but he also shows the opposite is happening: when our reason knows the correct probability, our emotional system could feel uncomfortable with that system 2 outcome and will adjust. Kahneman (2010, p.24, p.201) concludes that because of the way our thinking works 'we can be blind to the obvious and we are also blind to our blindness' with the consequence 'our almost unlimited ability to ignore our ignorance'. Taleb (2011) shows that indeed we do not think when making choices but rather use heuristics, and by using heuristics we filter out unlikely events. The interplay between system 1 and system 2 resembles Gödel's strange loop, well described by Hofstadter (1979) who refers to the different levels of a formal mathematical system, in which a higher level influences a lower level, while at the same time it is defined by this lower level. Such a self-reference could lead obviously to a conflict between the different levels, like system 1 and system 2 could have conflicting results in our brain.

Gladwell (2005) provides many practical examples of our unconscious thinking, our quick knowing, without knowing why, based on experience and pattern recognition and not arithmetic decision making. He describes how our unconscious brain is biased and often makes wrong judgments based on for instance length, skin color and gender, like our unconscious assumption that tall people are better leaders with the consequence that tall people are awarded higher income. This would fit Kahneman's explanation that system 1 represents categories by a prototype or a set of typical exemplars, which deals well with averages but poorly with sums.

The reason of this behavior of our brain system 1 may relate back to the time our brain was predominantly used for surviving, constantly scanning for food, for quick interpretation of dangerous situations, for deciding whether to take flight, freeze or fight. Though we need to be careful for oversimplification. In the sixties a popular hypothesis was the Triune brain (MacLean, 1973): a distinction between a so-called reptilian brain, a mammalian brain (i.e. the limbic system) and a human brain (i.e. the neocortex), that would have developed in that order. Although still popular among some psychologists, it turned out to be a myth. Later research showed that it is all much more complicated, and the 'reptilian' actions such as finding food, eating, moving and building a shelter, are relevant to all vertebrates. The limbic system turns out to be a quite diverse structure and not uniquely responsible for emotions. Moreover it seems there is no basis for saying that one part of the brain is older than the other.

The world was surprised by the experimental findings by Libet (1985) who showed that our cerebral cortex is already preparing motoric actions before our consciousness is aware of it. Swaab (2010) describes fMRI experiments (functional magnetic resonance imaging) that show a time gap of 7 to 10 seconds of motoric action preparation before we become aware of this action. From this we may conclude that we think much less than we think we do, and that we act without thinking. This has an immediate consequence on how we deal with information, in particular when we are in a hurry and do not think.

Swaab also describes another characteristic of our brain, the matter of reliability of information. When our brain does not receive information regularly, it starts filling in gaps on its own (confabulations). Our brain produces its own information. Similarly, in case a sense organ does not provide information on its own, our brain produces such information as came from that very sense organ. Notably we cannot distinguish between the real sense signals and the created ones; this is beautifully described by Sacks (2007) in Musicofilia. So we create our own information, without being conscious of it.

Humorous and shocking examples of how we fool ourselves with relative thinking are provided by Ariely (2012). The title summarize his conclusion very well: 'The honest truth about dishonesty, how we lie to everyone, especially ourselves'. For instance, we put much more energy in achieving a saving of 8 euro's on an article priced 15 euros than on an article priced 300 euros, whereas the gain is the same. And car sellers know people spend a much higher amount on leather seats in an expensive car than they would for a leather sofa at home because they relate the amount to the price of the car. So, we think in a relative, rather than an absolute and rational manner. People have many biases. The way we act on information changes once we are in a group, called pluralistic ignorance. One example is that all members of a group did not act when an outsider cried for help, while most would have helped individually. Another example is that people in a group could become violent if a few members are, whereas those individuals would not have acted this way on their own. People relate to the majority.

Finally, another perspective is the limitation humans have when it comes to the intake and processing of data. An observation by Moscoso Del Prado Martín (2009) shows that input/output processing time of humans is rather limited to 60 bits/s in a typical experiment; and Jensen (2006) found 25 and 36 bit/s in another experiment. These observations suggest humans need to be very selective with information intake. In contrast, the amount of information we are producing is increasing exponentially. Similarly Hinssen (2014) concludes that many processes in the brain occur automatically and our unconscious part of the brain really runs the body, with many decisions being made by our unconscious mind. He states that our senses collect 11 million bits/sec, our conscious brain can only process 40 bit/s. in our conscious brain we can recall 7 ±2 items at a time. The main goals of our unconscious mind were likely to be self-preservation, survival and replication of our genes/ourselves, but we learn and evolve. Whereas the growing amount of data and a world more interconnected suggest we get better informed, it could also overwhelm us and causing us to use more often the fast system 1 for decisions at the cost of accuracy. Therefore data interpretation and retrieving proper information from the rapidly growing amount of data is of utmost importance and necessary to consciously deal with this growth.

In summary, there is a tension between our unconscious mind and the rational thinking part of it. We think much less and differently than we think we do. We create information, stories and causalities that do not exist. Our quick brain prefers fast and easy answers, like heuristics. When it comes to statistics, we prefer averages and normal distributions of a simple linear world, while diverging distributions and probabilities of non-linear systems require tough thinking and power to go against mainstream thinking as our habit to relate to others may pull us back to the quick thinking of a group. Therefore we can easily miss or forget about accepted residual risks as we unconsciously rewrite our stories.

3.2 The way we deal with time

Time is an agreed physical quantity defined as the duration of an event and used to sequence events; it is measured in the unit second. Humans usually treat time linearly and/or cyclically, and also directionally. However our time experience and perception are often non-linear. Our time perception very much depends on what we go through: when in pain we believe time runs slowly, whereas when experiencing pleasure perceived time runs fast. Both pain and pleasure are remembered from the peaks, in particular the last one, as well as from the last experience of pain. They are not remembered by the duration. This relates to Kahneman's description of our quick brain function system 1, capable of dealing with norms, peaks and prototypes, but not sums. Rationally one would expect someone to prefer the shortest period of pain possible, however it turns out that system 1 prefers a bigger sum of pain as long as the peak and the end experiences are diminishing. It is probably caused by our memory that recalls both the most intense moment and the pain/pleasure at the end, but not the duration. This is why many movies end well, to avoid people believing it was a waste of time watching. A (financial) crises is usually recalled by the peak, not by the sum (of time or damage). We experience a crisis, but we recall something else because we build our own history (narrative fallacy). People choose by memory, and even deliberately feed the memory by making pictures, picking the news they want and creating their story. We seem to recall our experience mixed with our pictures and they are quite arbitrary, and then they fade and get rewritten.

Hofstadter (1979, p.177) created a rule to state the difficulty of estimating accurately the time it will take to complete tasks of any substantial complexity. His law: 'It always takes longer than you expect, even when you take into account Hofstadter's Law'. This law is a self-referencing time-related adage and the recursive nature of the law is a reflection of the universal experience of difficulty experienced in estimating complex tasks, despite all best efforts and including knowing that the task is complex. Hofstadter (1979, p.152) wrote: 'In the early days of computer chess, people used to estimate that it would be ten years until a computer (or program) was world champion. But after ten years passed, it seemed that the day a computer would become world champion was still more than ten years away'. He then suggests that this was 'just one more piece of evidence for the rather recursive Hofstadter's Law'. On the contrary, just slightly later it suddenly went so fast and Deep Blue won; much quicker than people thought. A similar case happened with AlphaGo, beating the world's best Go player in March 2016 (at 9th dan), only about half a year after the AlphaGo was 'only' at 2nd dan and the Go world believed the machine would not make top world level anytime soon. This illustrates how people conceive of progress in linear terms, when it is actually exponential. Our view of the future is therefore rather limited if we do not know or understand the type of process. By default we seem to have a tendency towards linear extrapolation of our history.

Taleb (2012) clarifies well how often people choose for the short-term benefits and neglect the (risk of) long-term drawbacks. One example is how we cope with our health if we don't think about the long-term consequences. Unhealthy eating and drinking (ingredients, amounts) give short-term pleasure but long-term pain. The same holds for quite a few medicines taken for short-term relief, with little knowledge of the long-term consequences. We value the long-term risk lower than the short-term pain, probably because we do not feel the long-term pain yet and have difficulties imagining it. Immediate use of fossil energy over long lasting pollution is a similar case, as are various short-term financial gains over long-term risk (of credibility). We tend to favor profit over endurance. This could explain why we neglect residual risks (as perceived to happen in the long-term) even when consciously accepted at the time.

The tendency for people to underestimate how much time they need to complete a task or project is called the ‘planning fallacy’, see Kahneman and Tversky (1979). They explain that it is mainly due to the optimism bias, a cognitive predisposition found with most people to judge future events in a more positive light than is warranted by actual experience. Buehler et al. (1994) show it only has an effect on your own tasks: it seems that people make a better estimate of the task completion time by other people, than of their own task. Even if people are called out and recognize their past predictions have been too optimistic, they still insist their current predictions are realistic. The likely explanation is that the outcome on time is easy to imagine, whereas the alternative of failure is harder to imagine and there are many ways a project could go wrong. It could be that people neglect their full experience or it is simply wishful thinking. A further explanation may be that people take credit for past successes and discount bad experiences that were clarified by external factors. People believe that they are less at risk of experiencing negative events compared to others, like a large majority of people believe they are better in many tasks than the average (which is impossible by definition), and believe that crime, illness, loss on investment will not happen to them. Further, a search for information that supports a positive view increases the bias. People are also telling an optimistic story as they imagine that it is what other people want to hear and that could well be a habit contained in culture.

Could the (effect of) optimistic bias be reduced? One would expect that experience leads to lowering the bias, but as shown by Buehler et al. (1994) people’s use of relevant past experiences is quite limited. A smaller distance between the subject and the reference group does reduce the bias. A solution to overcome the bias may be found in adapting a structural approach in planning and decision making. Flyvbjerg (2004) states that people ignore or underweight distributional information, i.e. data on variation from the expected outcome, expressed as standard deviation and variance. By improving planning and forecasting methods one could try to bypass the optimism bias; see also Flyvbjerg (2008). Decision making in IT projects and risk management would of course profit from models that are robust for the optimism bias.

Neglecting the long-term makes us vulnerable and sensitive to negative disruptions. From a more philosophical angle, Bregman (2013) describes the progression humanity makes is accelerating, but progression in the long run includes lots of progression traps, i.e. the sudden changes humanity faces which counts both for destruction and creativity. Like Taleb, he also signals that short-term benefits often lead to long-term drawbacks.

In summary, our perception of time is not linear and peaks are better recalled than duration. We tend to favor profit over endurance. The way we handle time could explain why we experience disruptive events as unexpected. The unknown events, beyond our imagination, fit the optimism bias for future events and plans. And the events that were imagined, the accepted residual risks, are perceived to be only long-term risks, or neglected and forgotten when indeed it takes a long time before an event materializes.

3.3 The way we deal with probability

It turns out we have limitations to deal with statistical distributions, averages, time, probability and uncertainty. Many of the psychological findings, the biases, are known from ancient times. Examples of biases are: hyperbolic discounting (prefer to receive one euro today rather than two euros next week); loss aversion (brain negatively affected by loss three times more than the joy of gain); holding to a loss position (people avoid scrapping failed projects/positions on-time); the paradox of progress (human nature knows no upper bound); cognitive dissonance (stress caused by inconsistency, usually reduced mitigated by a selective take of information); overconfidence; asymmetry between losses and gains; and endowment effect (difference between pain of giving up and pleasure of getting something; loss is more heavy than the pleasure the inverse gives).

Behavioral economics shows that people both overestimate and underestimate unlikely events. The overestimation happens when we well imagine the loss and consequence, like theft of luggage or damage of a smartphone. We treat the event as very plausible and consequently we are willing to pay in excess for certainty (such insurance policies sell well). Our brains violate the logic by confusing plausibility and probability. Kahneman (2011) refers to 'conjunction fallacy' when we judge a conjunction of two events to be more probable than one of the events in a direct comparison. He also shows the decision weight people assign to outcomes differs by probability of the outcome: low probability is overweighed (called possibility effect) whilst high probability is underweighted (certainty effect). The probability of an unlikely event causing a loss is overestimated particularly when the alternative is not fully specified, that is fear. From ancient times we have been wired to avoid risk and it is more costly to miss the signs of a predator, a threat, than to miss the signs of food, an opportunity. Consequently, our brain overestimates such threats and underestimates opportunities and resources.

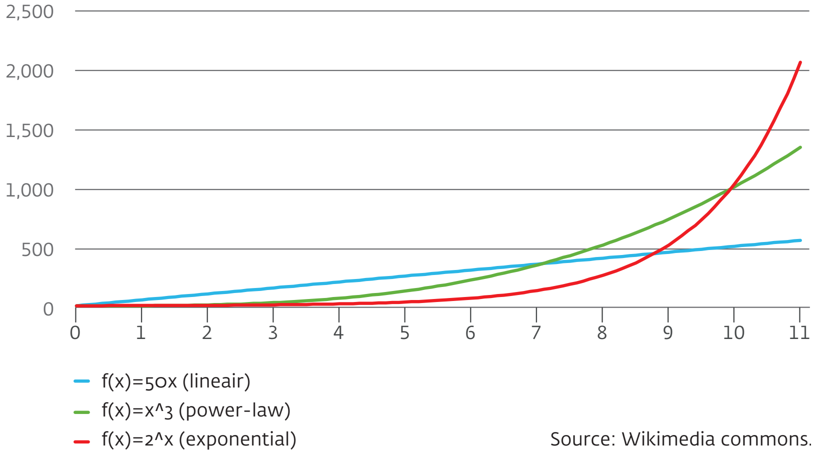
The second case, the underestimation of unlikely events, happens for rare events further away in time. They are perceived as less plausible or rather ignored, such as tail risk events. The explanation could be our system 2 consciously tells us a rare event may happen, though very unlikely, but as we lack experience of such a rare event we simply cannot imagine an outcome like that and we quickly answer a different question via our system 1 to forget about the rare event. We tend to ignore the odds of a flood, volcano eruption, meteorite impact because we cannot picture that situation or lack such specific history in our brain. When a crisis happened, we do have a picture of that crisis in our memories so we can imagine such rare event (the peak and ending are well remembered as stated before) and build constructions to prevent or lower the odds to that situation happening again. Still, we are not seriously prepared for different crises. This process is reinforced by our brains being vulnerable for group think. In groups there is little room for objective system 2 thinking: a majority gets easily the overhand with system 1 intuitive thinking and sets the outcome. The intuitive thinking is further supported through lobby, politics and amplified by some of the (social) media. This may cause irrational behavior and mismanagement. Quality media adds rational thinking back in the process, by showing facts and factual comparisons. Also universities, think tanks and authorities are in a position to present more factual (system 2) analysis to avoid the underestimation of unlikely events.

Averages are easily picked up by our brain. But we got to be careful when averaging in a space of uncertainty. Plans based on average assumptions are wrong on average. For example, a group of people planning to depart for a trip together agree to leave at a certain time from a certain spot. The group will usually not depart at the average arrival time of the individuals, rather they will depart at the arrival time of the last one (to mitigate the risk of waiting long people could agree at a cut-off time). Another example typical for IT projects: if each one of 6 software developers communicates he/she needs 3 to 5 weeks, on average 4 weeks, to develop a piece of code, decision makers could expect the code to be ready on the average 4 weeks' time. However one cannot average out the consequence of the uncertainty. The distribution of time lapses of the 6 developers will use the complete range of outcomes which likely will be filled with one or more developers in need of the maximum 5 weeks' time. Even if only one developer needs

5 weeks, the entire code cannot be ready earlier than 5 weeks. Consequently, the entire code of the 6 developers will most likely be ready not before the maximum of 5 weeks. One could use probability management tools to better prepare for the more likely outcomes and to overcome misjudgment.

Probability is hard to handle for the human brain. To calculate and apply the outcome we need to use our rational brain (system 2). Instead our fast brain replaces probability with similarity and plausibility. Bayes' rule describes the probability of an event based on conditions. This rule is used to calculate the odds. In practice, our brain rarely uses Bayes' rule, resulting in an overweight, underweight or even neglect of the outcome. We usually overweight the probability of the event for the condition met and neglect the probability for the condition not being met. Again, this is caused by our brain seeking a similar case following heuristics (and such a quick answer for a similar case would often be fine, but could also be plain wrong). An example by Kahneman (2011) on a relatively simple probability calculation based on two items of information: 85% of cabs in a city are green, 15% are blue. A cab was involved in an accident, a witness identified a blue cab at the accident and a court tested the reliability of the witness' testimony being 80%. What is the probability that the cab involved in the accident was blue rather than green? Many people provide the quick answer to say that the cab seen to be blue has a chance of 80%, as that is what the witness reported, taking into account its reporting reliability. However this way the base rate is being ignored. The correct answer is 41%. Taking the base rate into account, the witness reports in 80% of the cases (the reliability) a blue cab when it was indeed a blue cab (80%*15%), whereas the witness reports in 20% of the cases a blue cab while it actually was a green cap (20%*85%) which is more often. So the outcome is proper blue cab reporting as a fraction of total blue cab reporting (80%*15% / (20%*85%+80%*15%) = 41%).

Chart 3.1 Linear, power law and exponential functions



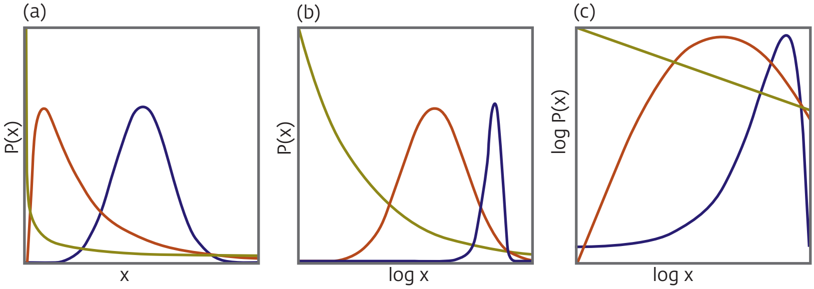
Source: Wikimedia commons.

Another challenge for the human brain is to imagine the consequences of exponential growth. We are often surprised by exponential growth, see chart 3.1. An exponential function, such as 2 to the power x, doubles with x+1. Growth in small numbers looks rather small and is therefore usually underestimated when taking off. A classic example is the growing number of waterlily leaves in a pond. Imagine the number of leaves doubling each day. With a tiny area covered you wouldn't notice much of the growth. Eventually the surface of the pond will be fully covered. The day before that moment, the pond was only covered half, and only one week before full coverage just one percent of the pond was covered. Whether you count bacteria, or customers using a new product, the initial small numbers stay under the radar for a while. People may call the new product a failure, because of the negligible numbers; however, it keeps growing and then it tips, surprises people and it is suddenly unstoppable. Recall that when it reaches only 1%, it is just about seven doubling steps away from the 100%.

And then we have distribution. Outliers can sometimes be neglected, sometimes not. It depends on the shape of the distribution of outcomes. Taleb (2010) explains this when comparing the effect of outliers (particular events away from average) in his so-called mediocristan and extremistan worlds. In a mediocristan world, one outlier does not affect the average; like the tallest man of a large group of people hardly influences the average height of people of that group. On the contrary, in an extremistan world an outlier does affect the average of the group, for example a top earner in an income distribution has a significant influence on the average income of a group, and is called a meaningful outlier.

Linear phenomena and averages are reasonably well handled by people. In the space of continuous probability distributions, we understand the well-known normal distributions (Gaussian distribution). A distribution is a mathematical description of random variables, for instance from experiments and surveys, showing the probabilities of events in a space of all possible outcomes. Examples of normal distribution are height, intelligence and blood pressure of humans. A second type of distribution is the log-normal distribution, where the logarithm of the random variables is normally distributed. The log-normal distribution is also known as the maximum entropy probability distribution. Examples are measures of size of living tissue (length, skin area, weight); file size of audio and video files; the length of comments posted in Internet discussion forums, the length of chess games, the size of cities and the size of cash payments and interbank payments. All common examples, but people have more difficulties understanding the distribution. A third common distribution is the power law distribution, where the log of the quantities is exponentially distributed (the cumulative distribution with a power law form is also known as Pareto distribution and follows Zipf's law). A power law functions is x to the power c, like x to the power three (chart 3.1). The power law distributions (approximately) occur in a wide variety of biological, physical

Chart 3.2 Distributions: (a) normal in blue, log-normal in red and power law in green; (b) and (c) show the distributions with log scales



Source: TRENDS in Cognitive Sciences.

and man-made phenomena, such as earthquakes, solar flares, moon craters, frequency of use of words in languages, number of papers scientist write, number of hits on web pages, sales of branded commodity, etc. In a normal distribution both sides are symmetrical and the slopes curve like a bell. Our system 1 can handle this. In a log-normal distribution the right-hand side of the curve has a more gradual incline, the diagram is called right-skewed. A power law distribution follows the typical asymptotic curve, with a long (fat) tail to the right. See chart 3.2. The log-normal and power law distributions have consequences for risk and growth, but they are not easy to imagine for people as their system 1 cannot deal with it but system 2 can. Misinterpreting distributions forms another reason why we are often not prepared for certain events. A simple conclusion of power law consequences is that major events happen rarely whereas minor events happen much more frequently. Power laws are natural but usually people fail to grasp the consequences.

To summarize, probability estimation goes easily wrong in situations where the distributions of outcome is not a normal distribution. Our fast brain is often right with averages and normal distributions, but we should only rely on real calculations when it comes to more difficult situations.

3.4 The way we deal with risk

Risk means to dare, derived from *risicare*. Descriptions on risk go back to the 17th century with Pascal's theory of decision making: the theory about deciding what to do when it is uncertain what will happen, and making that decision is the essential first step in any effort to manage risk. Bernstein (1996) calls it the remarkable story of risk, providing an important overview of risk, its history, the way we measure chance and how we deal with the results as well as ignore some. Bernstein (1996, p. 197) states that 'The essence of risk management lies in maximizing the areas where we have some control over the outcome while minimizing the areas where we have absolutely no control over the outcome and the linkage between effect and cause is hidden from us'. Risk equals likelihood multiplied by consequence. Classic risk management contains the following options to deal with risk, after identifying and evaluating them. One needs either to manage down the risk or exploit the risk to gain from the positive consequences of the situation. The options to manage it include 1) avoid the risk, stop certain behavior so you are no longer vulnerable to that risk; 2) reduce the risk, through taking measures or taking away the cause of risk, all at a certain cost; 3) transfer the risk, to another party causing that party to manage the risk, like an insurance; and 4) accept the (residual) risk, by consciously taking into account the consequences which should be regularly evaluated.

The way we deal with risk is rather biased, irrational and ignoring.
We saw that we get easily preoccupied with all kinds of risks with minor consequences and at the same time live unconsciously with much bigger

risks in daily life. We estimate the odds of being killed in a terrorist attack to be much higher than they actually are, compared to the much higher risk of being killed in a car accident or drowning in your own bathtub. The perception of risk is influenced by the relative amount of media attention it receives, as most media tend to report on what goes wrong in the first place, with emphasis on the bigger events involving mass casualties. There is hardly any mention of the risk to individuals taking place in and around the house, with (financial) consequences for society (work, healthcare). Small risks with huge impact, like a flood or an exploding chemical plant, are beyond the radar of many people.

In many cases we do insure ourselves against risks with small probability and high impact. A first example is that many insure against the risk of losing their house because of fire. The probability seems to about 0.1%, the maximum material loss is capped to the total loss of the house. Another example is the Dutch multi-billion euro expenditure on waterworks including evacuation plans in place for managing extreme scenarios. This is worth the investment as it protects millions of lives against the risk of floods, with probabilities between 0.01% and 0.1%. In this case the maximum loss is practically speaking not capped, as tsunamis in various places in the world have demonstrated. It is important to use methods to put probabilities and impacts in perspective and make them comparable. An example of an overall risk comparison is the Dutch national all-hazard survey of potential threats and disasters that could disrupt society (Nationaal Veiligheidsprofiel, 2016). It provides an overview of the most important risks to national safety and uses one classification method of risk in order to make a diverse set of disasters, crises and threats, comparable.

The most popular and traditional measure of investment risk, is volatility. Volatility is measured irrespective of the direction an investment moves, while investors' concern is about the worst-case scenario, regarding the question "how much could be lost?" Value at Risk (VaR) is a popular measure of that risk and has become the standard measure of market risk in risk management, see Jorion (2001). VaR estimates how much a set of investments may lose, usually with a 95% or 99% level of confidence and given normal market conditions in a certain time period. The VaR is thus expressed as a probability that a loss will not exceed a certain threshold. As a consequence, for the remaining 5% or 1% probability loss will be higher than that threshold and it may be hundred times higher than that threshold. It is uncapped, it simply does not specify how much higher. The representation in a few numbers makes it an easy to handle model and useful tool, in normal times and in the normal range of the given probability, which occurs most of the time. Although its usefulness and weaknesses are widely discussed in literature, some of the assumptions and consequences need to be analysed further as they provide relevant answers to the main question of this paper.

As VaR works under normal market conditions, which occurs most of the time, people trust this model. However this turns out to be a false confidence because in extreme events one may lose far more than the VaR amount indicates, as has been experienced in the financial crisis. What if market conditions are not normal? VaR assumes mark-to-market pricing, but in extreme market conditions market prices may be unavailable. VaR measures assume that the current portfolio is frozen over the horizon, but trading portfolio evolves dynamically and under abnormal conditions investors (algorithms) do trade. VaR assumes limited time horizon, which leaves certain long-term risk out of the model. VaR is a static measure of risk, whereas an evaluation of risk at different times, i.e. dynamic risk, would contain valuable information. VaR is not sub-additive, i.e. the combined risk of a portfolio may exceed the sum of the VaRs of the components of the portfolio. Altogether, VaR does not say anything about the remaining open-end risk and of course it is key that risk management stays alert to acknowledge the moment VaR is no longer of use and to use other tools and measures.

Actually well before the latest financial crisis, concerns over VaR were voiced in a debate back in the nineties in which Taleb (1997) and Jorion set out some of the major points of contention on VaR. Taleb claims VaR ignores 2,500 years of experience in favor of untested models built by non-traders, he describes some of the problems. Jorion defends VaR as a good estimation of risk, not perfect, but the best we have. What is interesting about this debate is that both agree that traders may have incentives to game their VaR and choose investments that seem to have low risk (in VaR) for the wrong reasons (e.g. the Mexican Peso in 1994 had low volatility and therefore scored low risk despite the high devaluation risk). Taleb states that the risk management objective function is survival, not profits and losses. So Taleb (1997, rebuttal) concludes that the statements 'VaR generally works' is useless, as it could mean the trader 'made $8 million in eight years and lost $80 million in eight minutes'.

Similarly, Einhorn (2008, p.2) concludes that VaR has focused on the manageable risks near the center of the distribution, but basically ignores the tails. He argues the assumptions provide a false confidence of the VaR outcome which even leads to higher risk taking. He posited that VaR led to excessive risk taking and leverage at financial institutions and created an incentive to take 'excessive but remote risks'. Einhorn (2008, p.2) compared VaR to 'an airbag that works all the time, except when you have a car accident'. In an extensive New York Times article Nocera (2009) provides interesting insights in the history and the use of VaR during the crisis. He concludes VaR exacerbated the 2008 financial crisis by giving false security to bank executives and regulators. Firms that were aware of the 1% unlimited risk believed they could not afford to be the first to withdraw from

the market because they would lose out to their competitors who still gain until an extreme event happens, whereas in the long-term an extreme event would hit everybody and the firm would not be blamed in particular. This reasoning leads of course to dangerous behavior. He views VaR a powerful tool but easy to misunderstand and dangerous when misunderstood.
Of course you can't blame the tool, but the way it is (mis)used. Like Keynes already considered that economics is not like natural sciences and had the insight that to convert a model into a quantitative formula is to destroy its usefulness as an instrument of thought. To summarize, VaR measures do not include the greatest risk of all: big events with very small probability, like discrete changes and phase transitions. Risk measures should be broadened in scope to cover high impact events, be it black swans, dragon kings or other.

An alternative to VaR that is more sensitive to the shape of the tail of the distribution is Conditional VaR, also called Expected Shortfall. It calculates the weighted average of the losses that occur beyond the VaR cut-off point in the distribution. Analyzing the reliability of the two risk measures Danielsson and Zhou (2016) found that risk forecasts are extremely uncertain at low sample sizes, with Value-at-Risk more accurate than Expected Shortfall. They also mentioned the methods give banks some scope for deliberately underreporting risk without violating regulations and control mechanisms.

Alternatively, the Extreme Value Theory (EVT) from the statistics discipline is sometimes suggested to have the potential to deal with extreme deviations. It seeks to assess the probability of events that are more extreme than any previously observed.

However, the EVT assumes a continuous function (on a simple sinus-shape continuous function it is easy to imagine that continuous functions contain at least one value where the function reaches its maximum and at least one where it reaches its minimum), whereas discrete changes and phase transitions are not covered. Some research has been done on extending it to semi-continuous functions, like extreme events caused by earthquakes. EVT is concerned with extreme tail behavior (e.g. one per mil) and only looks at the tail events. EVT estimates quantiles and probabilities beyond the usual range of observed data, using only the extreme event data rather than all data but very few events remain a challenge in statistical methods. An EVT solution is investigating data in an intermediate area next to the tail and extrapolating the found properties to the tail area. For application in financial risk management, Diebold et al. (2000) show some limitations and pitfalls, to name the selection of such intermediate area as well as the validity of the assumptions in EVT. Financial data is often not independent and identically distributed rather serial dependent like volatility clustering. De Haan et.al. (2016) describe a way to deal with the two critiques and provide adapted EVT methods that overcome the two issues jointly. They show estimators for high quantile and extreme value index remain stable, even for data sets with serial dependence feature. The trade-off between high variance with a few observations and a bias when more observations from a larger area are used, is compensated with a bias correction.

In conclusion, people have difficulties dealing with risk because of the shortcomings we have with estimating probability as well as imagining impact. It requires proper thinking and planning to cater for the less likely events. The most known risk measure method for investment risk is VaR which seems to works fine under normal circumstances however does not include the biggest risk of all, it does not inform us about the exceptional situations with very small probability and very high impact. Extreme Value

84 Theory may be of help, and recent studies indicate some progress. But to deal with discrete changes and other discontinuities we need other tools to cover the whole spectrum of probability.

3.5 The way we deal with uncertainty

According to Keynes (1921, p.2), there is a difference between what is definable and undefinable in future: 'The terms certain and probable describe the various degrees of rational belief about a proposition which different amounts of knowledge authorize us to entertain. All propositions are true or false, but the knowledge we have of them depends on our circumstances'. He did not distinguish categorically between risk and uncertainty. Knight (1964) did, he defined uncertainty as 'risk that is immeasurable' which means it is not possible to calculate uncertainty whereas risk in this sense is computable. Following Knight's distinction, risk applies to situations where we do not know the outcome of a given situation, but we can accurately measure the odds. Uncertainty, on the other hand, applies to situations where we cannot know all the information we need in order to set accurate odds in the first place. That makes risk being measurable uncertainty, whereas true uncertainty cannot be measured. Some believe this distinction is too strict and hardly workable, as almost all situations are complex and contain uncertainty. This risk definition would only work in a highly controlled environment, like in games of chance, leaving all other cases as uncertain.

About a century ago Knight and Keynes analyzed the areas of uncertainty and probability, and the effect on decision making. They both questioned the value of decisions based on the frequency of past occurrences. According to Bernstein (1996), there is still the controversy whether best decisions are either based on quantifications and numbers from past experience or based on more subjective beliefs about the uncertain future. Chaos theory teaches us that the value of the numbers from the past have their limitations, in particular the averages that we extract from these data. That means Galton's regression to the mean, which we intuitively often use, makes little sense in a world with non-linearities; e.g. an exponential function runs away from its average. At the same time, all events do depend on earlier steps, so the past is relevant. How they depend, varies with the dynamics of the system, results don't need to be proportionate to the cause, as shown in chaos theory.

How do we deal with uncertainty? The British philosopher Carveth Read said: 'It is better to be vaguely right than exactly wrong'. That sounds very much common sense, but it is not what usually happens. Many of us cannot handle the uncertainty of being vaguely right. Policymakers and boardrooms often expect exact estimates of project costs, GDP growth, purchase power effects, etc. Many economic models deliver exact estimates, which pretend accuracy because of the use of formulae. Precise math delivers precise outcomes which suggests right answers fit to communicate. However, we usually do not know how mistakes in assumptions, incomplete input information and uncertainties propagate through a model. Even small changes may lead to an outcome that is way off because of non-linear effects. Moreover, larger ranges of uncertainty feel uncomfortable to communicate, as many of us fear uncertainty as it suggests we do not know, while we want to be in control and show it. A clear example is the global warming debate, where decision makers decided to set a maximum of two degrees Celsius to the world average temperature increase: a precise number showing they are in control to steer our planet's climate. A clear goal is probably intended to free up budgets and get people moving, but it feeds an immodest attitude of being in control of a system we cannot control. Geologist Kroonenberg (2006) puts the human role in perspective, showing world's climate changes all the time, with much higher temperature and carbon dioxide fluctuations in history, well before humans caused pollution; people actually feared global cooling only half a century ago. His message is humans are not in control of earth, we greatly overestimate our role in nature and we better adapt to

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the climate, like we do with seasons, instead of haughty, useless and costly decisions to steer it. Similarly Bak (1996) warns about not making the same mistake as with the Club of Rome 'The Limits to growth' study from the seventies, when unpredictable factors were not incorporated into the model and wrong conclusions were drawn. This means we should take a much longer time scale perspective and dare to communicate the uncertainty we face in understanding our systems. Such uncertainty justifies for instance an energy policy, with reduction of pollution and start using alternative sources of energy, however does not justify a climate policy apart from adapting to the climate.

Hinssen (2014) describes that most things are uncertain, though we search for certainty. He states that the big disadvantage of models is that they cannot handle uncertainty and proposes to keep as many options open as possible to be prepared for the unknown (he illustrates that in WWII the French were centrally planned and organized, and therefore beaten by Germany that could attack by surprise as it better managed uncertainty). He provides several examples to show the world is complex, networked, adaptive and not linear causing lots of uncertainty. We got to focus on the emergence of patterns and realizes that many networks, such as roads as well social networks, are created without a grand plan.

There is a challenge in communicating uncertainty. The brain seems to interpret uncertainty similarly to fear and we know people run away from fear (system 1). Transparent communication to the public with revealing the underlying uncertainty, risks losing the connection with the part of society that is not willing to think or take advice about the issue. In that case, the message blurs and the fear and negative thoughts caused by the uncertainty lead to the message being rewritten to a fictional but coherent story easier to memorize, as shown before. After all, the human brain prefers a coherent story over a true story. So the communication of observations and uncertainty should go along with a well-thought message or action to take.

What about the experts? Professionals should recognize situations of uncertainty and should know what we know and not (yet) know, where the difficulties pop up and what is impossible to know and to forecast. Experts should know and indicate where the limits of their expertise lay. However this is also difficult as the expert is expected to know by the virtue of being an expert and as said uncertainty is not easily communicated and admitted. So there is a fear for not knowing as it could be interpreted as a weakness that the work was not (properly) done. This is the expert problem and keep in mind you are worse off being misinformed than uninformed. Confidence is usually valued higher than uncertainty. The same holds for a physician: people want to hear an explanation and get treatment, rather than an explanation about the factual uncertainty and the advice of not yet starting a treatment. The physician risks being replaced when exhibiting relatively more uncertainty. Meeting expectations prevents people from admitting the uncertainty. A way to deal with uncertainty is to keep the uncertainty throughout the model and to perform sensitivity analyses to find out the systems' most vulnerable triggers. It is usually better to focus on the most important parameters and not too many, and steer in small steps.
In summary, uncertainty in the Knightian sense is defined as immeasurable risk. Subjective beliefs about the uncertain future could be more important in decision making than numbers from the past as we most often don't know the proportionality between cause and effect. Uncertainty is hard to communicate and risks interpretation of fear and being translated into a coherent story rather than sticking to the facts, observations and true message. We want to be in control and show it; confidence is usually valued higher than uncertainty. Experts should indicate where the limits of

knowledge and expertise lie, perform sensitivity analyses of the systems, show the most important parameters and keep as many options open.

3.6 Understanding the system

The philosopher Bertrand Russell (1912) has described the problem of induction, or problem of inductive knowledge. It is a major problem in life: how can we logically go from specific instances to reach general conclusions? How do we know what we know? And how do we know that what we have observed from given events is sufficient for us to figure out their other properties? It leads to the questions of whether and how we can know the future, given the knowledge of the past.

The importance to answer these questions and the importance to really understand the system are clearly illustrated by Perrow (1999, first edition 1984) in his analysis of accidents, related to high-risk technologies. The accident at the Three Mile Island nuclear plant provided the basis for Perrow to analyze accidents in high-risk technological systems. He classifies systems in the way they are coupled (loose or tight) and their complexity (simple or complex) and claims accidents are inevitable in systems that are both tightly coupled and complex. He therefore refers to 'normal accidents' in such systems.

Tightly coupled interactions have no slack, and consequently no time to adjust or recover, with propagation of errors as a result. By complex, Perrow means incomprehensibility, the system is no longer fully understood. It seems there was no clear definition of complex systems at that time yet. His analysis took place in the early eighties, before more precise descriptions of complex systems emerged, among them at the Santa Fe Institute (founded in 1984). He distinguishes linear systems, being simple from non-linear systems, being complex. Complex interactions are 'those of unfamiliar sequences, or unplanned and unexpected sequences, and either not visible or not immediately comprehensible', compared with linear interactions that are 'expected and visible even if unplanned' (Perrow 1999, p.78). In line with later definitions, he views complex systems as having a high degree of uncertainty, lack of central control, whereby small events could cause big changes. However, no clear view of agent interactions, emerging patterns and self-organization are described. He recognizes a fighter plane being anything but simple, though linear, a system we would now call complicated, as opposed to complex. The cause of accidents in tightly coupled complex systems is the interaction of multiple failures that are not in a direct operational sequence. A few small bugs may cause serious malfunctioning, whereas each of the bugs are not enough to disturb the system. These normal accidents are failures that are inevitable in such systems. His analyses are based on accidents in man-made systems such as nuclear plants (in particular the Three Mile Island nuclear accident), aircraft crashes and dams. Perrow views accidents forming an inherent property of complex systems, they are embedded in the system. There is no control, the operator cannot be blamed, as he cannot understand and therefore control the system.

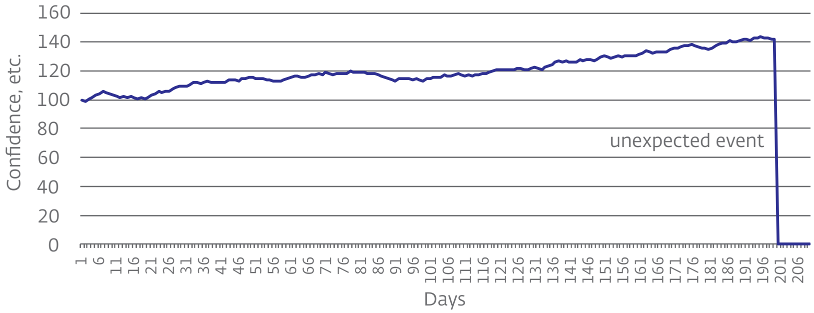
Perrow's advice to deal with the tightly coupled complex systems is quite rigorous, namely to simply abandon them. To add redundancy to such systems could be of help if it is part of the original design, but if added to the system at a later stage, such as after facing problems, causes additional risks as 'the more redundancy is used to promote safety, the more chance for spurious actuation' (p.260). Some openings are given to more nuanced ways of dealing with the problem, by improving our understanding of the system, reducing the size to minimize damage and by deconcentrating high-risk situations. High-risk deconcentrating seems to be a sensible thing to do, as shown with the distributed set-up of the internet and the diversity and non-tight couplings of internet content providers. This approach would help any infrastructures, among them the financial infrastructure, to improve the resilience of the total system. In the afterword of the 1999 edition he views the financial system as a complex and tightly coupled system. The growing global connections and increase in speed and automation in trade cause complexity and tightness to become stronger. Mezias (1994) considers the saving and loan crisis in the US as a 'normal accident' that fits Perrow's theory of the combination of highly complex and tightly coupled.

The information theory leading to digitization allows for much faster processing and tighter relationships between processes and actors, than was the case before automation. The distribution of IT-based solutions through highly connected networks potentially tightens everything together. The mix of IT and networks risks the creation of systems that are very complex and tightly coupled, and thus vulnerable to accidents. In their answer to The Queen's question: 'Why had nobody noticed that the credit crunch was on its way?', Besley and Hennesy (2009, p.8), on behalf of the British Academy Forum, wrote 'the difficulty was seeing the risk to the system as a whole rather than to any specific financial instrument or loan. Risk calculations were most often confined to slices of financial activity, using some of the best mathematical minds in our country and abroad. But they frequently lost sight of the bigger picture', they view not understanding the risk to the system as a whole 'a failure of the collective imagination'.

Another example to show the importance of understanding the system is given by Taleb's (2010) description of the life of a turkey (the original example by Russell was a chicken). A turkey is fed every day, and every single day feeding confirms the bird's belief that it is the general rule of life to be fed every day. On the day before Thanksgiving something unexpected will happen to the turkey, a so-called phase transition, when it is slaughtered (see chart 3.3). Consider that confidence increases with each extra day of feeding and that the feeling of safety just reaches the maximum when the risk is at the highest point. In other words Taleb (1997, rule No. 7) says: 'the fact that someone never died before does not make him immortal'.

Obviously many parallels can be described when our beliefs are confirmed doing the right thing every day until a sudden change happens. The turkey example also shows we may believe having the overview, based on past events, but the expected (linear) consequence may suddenly not happen. A possible disruptive event can always happen, despite of our built up confidence from the past suggesting a decrease of likelihood. This clearly shows that the absence of evidence is not evidence of absence. The perspective is important: to the farmer the slaughtering is not a disruptive event. The turkey does not fully understand the underlying mechanisms of the system. This essentially refers back to the philosophical question of how we know that what we have observed from given events is sufficient for us to figure out their other properties.

Chart 3.3 The unexpected event after slow buildup of confidence



Source: Taleb.

Phase transitions are well known from physics. For instance, when at a certain rise in temperature solid substance suddenly becomes liquid, and at an even higher temperature a liquid suddenly turns to gas. These phase transitions are reached by tuning a parameter, such as temperature. In physics, we found what the mechanism is, but a phase transition is a more general phenomenon. Newman (2006) describes critical phenomena, i.e. when the scale in a system diverges towards a critical point and the system experiences a phase transition. He shows the example of a model for forest fires caused by lightning: with small clusters of trees, forest fires have little effect on the forest. However if no lighting strikes for a while, more trees will grow and the clusters of trees get larger. Next, when the lighting strikes, the cluster is gone. Newman shows with his so-called percolation model that the distribution of cluster sizes follows a power law and the size of clusters and the size of fires converges to a power law. It turns out that with the increase of probability that trees occupy an empty spot, clusters get larger, until this percolation probability reaches a critical point (at probability 0.5927462…). After the fire the whole story repeats, again until that critical point. At that critical point the system turns out to be vulnerable, i.e. the system oscillates right around the critical point. The model is called self-organized criticality. Self-organized criticality was first described by Bak et al. (1987) and visualized with the sand pile model, which is a cellular automaton: the slope of a pile builds up when sand is randomly added, until the slope exceeds a certain threshold value and collapses. Self-organized means organized behavior arises without an internal or external controller or leader. Self-organized criticality is also used to model earthquakes, solar flares, biological evolution and avalanches, see Bak (1996) in which he describes the phenomenon in a broad sense. Bak et al. (1987) show a difference between phase transitions in physics caused by the change of a parameter (like boiling water) and phase transitions after reaching a critical point. The driving force is likely dissipation. The critical point in these dynamical systems is like an attractor, automatically reached by starting away from equilibrium. An attractor is defined in mathematics as a set of numerical values to which, for a wide variety of starting conditions, the dynamical system evolves. It looks like these systems organize themselves towards a critical point or state. A main question in understanding a system is to know what the attractors are.

We do not know when lightning strikes, but we know it will. The timing is beyond our control, so the aim should be to work on limiting the impact. Using Agent-Based Modelling, Miller and Page (2007) show implementations of the forest-fire model using different dynamics of agents' behavior to reach an optimal macro outcome. They show that different levels of adaptation impacts behavior and optimal system outcome, by distinguishing between homogeneous and heterogeneous adaptation of agents (trees). In the former one, agents adapt to maximize productivity, and a critical value is reached. Thus adaptation leads the system to a state that is both optimal and fragile. In the latter one, agents are allowed to differ their growth rate resulting in the emergence of firewalls and increased productivity, both without central planning. So this model shows higher level phenomena arising from lower-level interaction, increasing productivity and at the same time making the system less fragile. They suggest adapting the model to analyze bank failures. This also shows the importance of sufficiently understanding the underlying mechanisms of the processes and systems we create and not underestimating the variety of the dynamics and possibilities to steer.

Taleb's (2010) black swans are the extreme events that are rare, unexpected and something never considered a possibility. These events appear on the fat tail of the power law distribution. Newman (2006) shows power law distributions are self-similar, scale-free distributions, i.e. they are similar to a part of itself, and both small, regular and extreme events belong to the same distribution and origin from the same mechanism. Taleb considers black swans to be unpredictable in general, the final size of such a future event cannot be forecasted in advance, but one could prepare for the unpredictable event. Taleb says 'any system susceptible to a black swan will eventually blow up', which sounds familiar to Murphy's Law. Could a black swan be a phenomenon indicating we do not sufficiently well understand the system? Both black swans and self-organized criticality could start very small and growing but remains initially hard to notice, until it develops following the power law into a large or extreme size event. Sornette (2003, 2009), who explores the great challenge of predicting crises in stock markets, questions whether extreme events are due to the same mechanism. He argues that the power law paradigm may miss an important population of events and he therefore invented the notion of 'dragon-kings'. A dragon king is a metaphor for an event that is both extremely large in size or impact (a 'king') and born of unique origins (a 'dragon') relative to other events from the same system, but different than black swans. Sornette (2009, p.1) defines dragon-kings as 'meaningful outliers, which are found to coexist with power laws in the distributions of event sizes under a broad range of conditions in a large variety of systems. These dragon-kings reveal the existence of mechanisms of self-organization that are not apparent otherwise from the distribution of their smaller siblings' and views them as 'extreme events that are statistically and mechanistically different from the rest of their smaller siblings' which 'opens the way for a systematic theory of predictability of catastrophes'. Sornette hypothesizes that many of the crises that we face are in fact caused by dragon kings rather than black swans, i.e. they may be predictable to some degree. Such extremes are interesting because they may reveal underlying and hidden organizing principles, although significant uncertainty will remain present. Sornette (2003) studied the critical events based on the hypotheses that (financial) bubbles can be diagnosed in real-time before they end; and the termination of (financial) bubbles can be confined using probabilistic forecasts. He performed tests on the biology of pregnancy, on glaciers, and particularly on the vast amount of data from stock markets over the last few decades, and found that a class of critical events can be predicted based on the various signals of his algorithms and thus qualify as dragon-kings and not black swans.

Extreme events are hard to imagine for people before they have ever happened. Equity markets going down by 30 percent, tsunamis over 500 meter high, massive cyber-attacks, etc. The least we can do is to be vigilant for the dragons as they will hurt us, but it is better to put an effort in understanding the dynamic system and its non-linear behavior. Non-linear systems are very common, linear systems are actually the exception. Non-linear dynamic systems are sensitive to initial state and are path dependent, which means it does matter what happened before. Path dependency typically occurs in a network when a small advantage attracts more followers, creating a further benefit for others to adhere to this solution. These phenomena are difficult to work with and the mathematics has only been developed relatively recently. The famous French mathematician Poincaré discovered deterministic chaos in dynamic systems and developed the math. A chaotic system is deterministic, but never exactly repeats itself; it is bounded, usually has only few degrees of freedom and may lead to bifurcation. That is when a dynamic system changes qualitatively the nature of its behavior. A small change of a parameter could cause a sudden change in behavior of the system. It is only since we have powerful computers that we can model and get a better understanding of such systems.

To conclude, many systems are non-linear or complex and include discontinuities, like phase transitions. It looks like nature organizes itself towards a critical point. Systems we created show similar behavior with higher level phenomena that we do not like, often not fully understand, but that arise naturally from lower-level interactions in the system. Systems that are very complex and contain tightly coupled components, through the network, show behavior that we cannot control, oversee and predict. We have to better understand the existence and consequences of dynamic systems and their non-linear behavior, such as critical points and phase transitions, in order not be surprised like a turkey.

3.7 Limitation of the models of mainstream economics

In search of answers to the main question of why people often experience disruptive events as unexpected, it is important to also look at the economic models in use, quantitative, qualitative or stochastic models. If a model can never produce a disruptive event as output, than we should be aware not to rely much on that model under all circumstances, as we would never know when and in what circumstances such an outcome would be missed. If a model could forecast such an event it may be caused by limitations in the input or in conditions applicable to the model. Mainstream economic models usually assume a market tends to equilibrium, which may be a root cause of forecast failure. This classical concept of general equilibrium theory assumes supply and demand are balanced, in one market as well as all markets simultaneously (Cournot, Walras) and assumes in principle no external influences and the behavior of agents should be consistent and without incentive to changes. It further assumes stable markets, rational human behavior and information availability immediately to all agents. We know these assumptions are unrealistic. The wide use of the ultimate escape clause ceteris paribus summarizes well the lack of reality of the economic models as of course it is never the case that other things remain constant. Today's dominant economic thoughts, using models like dynamic stochastic general equilibrium (DSGE), Real Business Cycle and Arrow-Debreu models, still assume the economy is an understandable and equilibrium-seeking machine. In this paper this is viewed as traditional thinking.

The assumptions of traditional models (tendency to equilibrium, full information, control, rational behavior) were understandable at the time they were put forward, and this was the only way to make calculations with the available mathematics at that time. Mathematically elegant, but tendency to equilibrium puts a strong filter on what you can see: strictly taken, it allows no scope for exploration, creation, transitory phenomena, structural change, innovation and history. For a while, economists wished to align economics with the exactness of physical science from Newton. But physics continued with relativity, speed of light (the very big), thermodynamics, quantum mechanics (the very small), dynamical systems and chaos theory. Also in economics, the models were improved and time and other dynamics were introduced in the models, but unfortunately, attention to non-linear behavior is rather limited. It turns out to be hard to move away from the assumptions of traditional models. In recent years more attention has been paid to behavioral economics, with names like Marshall and Robins who studied the aspects of human behavior. Behavioral economics moved away from the traditional assumptions by taking into account non-rational behavior of economic actors, market inefficiencies as well as earlier mentioned heuristics and psychological biases. For example, game theory was developed to deal with the more common situation of incomplete information as opposed to the traditional assumption of complete information. However, for relying largely on data from surveys and experiments, behavioral economists received criticism from traditional economist.

Keynes (1921) already warned of inherent instabilities in markets and the possibility that markets fail to self-correct. Analyzing the impact of debt on system behavior, Minsky (1992) found the empirical positive feedback loops of inflation (feeding inflation) and debt-deflation (feeding on debt-deflation) as a support for his financial instability hypothesis. He stated 'the economy does not always conform to the classic precepts of Smith and Walras'

(Minsky, 1992, p.2). Other well-known critics came from Kindleberger, already back in the seventies. The Economist (2003, p.1) brought his work to the attention as ‘never been more pertinent’, referring to his criticism on the growing reliance on too narrow rational models and growing reliance of economists on mathematics. Later, after stock market crashes, the efficient market theory came under further attack. Behavioral economists saw the market bubbles as evidence that the markets are irrational and not perfect. Others argued that we lack understanding of the fundamentals of valuation of securities, but the question remained why rational investors do not arbitrage away bubbles.

Economic forecasts are usually communicated through precise numbers, often without a range of uncertainty, which of course cannot be realistic given the limitation on both the input, the assumptions and the model itself. An assumed sense of accuracy without range of uncertainty poses a risk to decision making. Indeed, the close relationship between economic theory, with amoral valuation of goods and services, and its use in practice for political purposes distorts the pure economic profession. When politicians demand a calculation of the economic effects of their proposals, they want clear numbers that are easy to communicate and which support their political goals. This leaves little room for uncertainty. This presents a trap for economists who dare not express the limitations of the models and the uncertainty that goes with them.

Rodrik (2017) addressed the issue of critics on economic modelling by pointing at overconfidence from economists about the model they use. He stated that the real failings originate from behavioral and sociological aspects of the economic profession, from mistaking a model for the model, from having a categorical preference for certain axioms, from having a preference for questions that are amenable to available tools of analysis and from implicit political-economy theorizing in policy discussions. He proposes a more humble attitude about how much economists know, recognition of economics as portfolio of models (rather than looking at the model) and being open to developing new models. Besley and Hennesy (2009, p.9), on behalf of the British Academy Forum, acknowledge the models don't work when you need them the most: 'These views were abetted by financial and economic models that were good at predicting the short-term and small risks, but few were equipped to say what would happen when things went wrong as they have'. However, even short-term forecasts require quarterly updates as was shown with an example in the introduction (chart 1.1).

Many economists admit they did not see the last economic crisis coming, as with other crises, and some wonder why economics seems to be blind to failures or crises in a market economy. Shiller (2015) said 'economists failed to forecast most of the major crises in the last century', as was the case for previous severe crises. But as he argues, doctors also fail to predict diseases. This suggests we may not expect proper prediction, but why do economists then produce so many economic forecasts? The failure of prediction has also been demonstrated in the study by Loungani (2001) who found that only two of the 60 economic recessions that occurred over the sample period 1989-1998 were predicted a year in advance (see introduction). Besley and Hennesy (2009) write that many people did foresee the crisis, however, the form, timing and ferocity were foreseen by nobody. There were certainly warnings about imbalances and risk in financial markets, but seems hard to act, change and avert a crisis. There also seems to be a kind of acceptance, to deal with consequences when they arrive, as stated by Besley and Hennesy (2009, p.9): 'There was a broad consensus that it was better to deal with the aftermath of bubbles in stock markets and housing markets than to try to head them off in advance'. Part of the explanation could be that nobody really had the overview of total risk to the system. Like Perrow's (1999) observations on complexity and tightly coupled interactions, that leads to a system that becomes vulnerable to unknown risks and accidents and no single authority has the overview of the system, is in control or has jurisdiction.

The recent economic crisis made very clear that the models didn't work. In a speech drawing lessons from the crisis for macroeconomics and finance theory, Trichet (2010, p.7) said 'When the crisis came, the serious limitations of existing economic and financial models immediately became apparent' and 'As a policy-maker during the crisis, I found the available models of limited help. In fact, I would go further: in the face of the crisis, we felt abandoned by conventional tools'. The key lesson he draw was 'the danger of relying on a single tool, methodology or paradigm. Policy-makers need to have input from various theoretical perspectives and from a range of empirical approaches'. He calls for learning from other disciplines which already recognized the complexity of systems, using agent-based modelling in economics and taking into account the non-linear behavior of the financial system and its pro-cyclical build-up of leverage and vulnerabilities.

In 'The Origin of Wealth' Beinhocker (2006) describes in a clear and rather confrontational manner the limitations of mainstream economic models. He describes the shortcomings, explanations and consideration for alternatives. He explains that presently used models lead to incorrect predictions and under- and overestimation of economic indicators. Obviously simplified economic forecasts, presented with exact numbers, even for long-term parameters such as economic growth, suggest we know what is coming, and government policies are based on such economic predictions. Indeed, the precise numbers provide, unjustifiably, comfort because of their ease of use in politics and communication. We all know how often these numbers are adjusted, while sudden changes are rarely forecasted. With wrong models we draw wrong conclusions and make wrong policy decisions. It is like getting the wrong diagnosis from an oversimplified medical test. The example in the introduction of the multiple revisions of IMF's world trade forecasts also shows the magnitude of the inaccuracy: real world trade was only half of the 5.5% forecasted 2 years earlier (see chart 1.1) so the error is in the same magnitude as the bandwidth of the quantity measured. It is likely that the longer term economy cannot be predicted at all, but people need predictions because we do not like uncertainty, and predictions do work for the physical world like seasons and gravity. Beinhocker states that the neoclassical model that lies at the heart of traditional theory was built on a misused metaphor. Without realizing it and with the best intentions, the late-nineteenth-century economists borrowed from physics a set of ideas that fundamentally misclassified the economy as a closed equilibrium system. He says a system in equilibrium lacks the internal dynamics to respond to its environment and will slowly die, a system in chaos ceases to function as a system. System dynamic studies indicate that the most productive state seems to be at the edge of chaos, a zone between stability and chaotic turbulence. That's where there is maximum variety and creativity, leading to new possibilities and the best chance for survival.

In an article in the Financial Times Taleb (2007) makes a firm stand against some of the financial economics that do not take into account rare events: Markowitz's portfolio theory would be incompatible with rare events like a stock market crash. He warns that business schools still teach these theories while lessons from market crashes and booms are ignored. It seems we do not learn from rare events, continue to employ the same models and are again surprised by the next rare event. Being misinformed is worse than being uninformed. Taleb (2010, p.252) also expresses criticism on the Black-Sholes formula and variants, that assume normal distributions and take standard deviation as the measurement of risk. This equation for calculating the value of derivatives has become the industry standard as it is easy to use and it produces precise prices, though its limitations were clearly stated. The price of an option is derived from the directly measurable quantities time, asset price and risk-free interest, supplemented with an estimate of the volatility. The volatility is probably hardest to estimate and could have a large effect on the resulting option price. The model assumes volatility to remain constant over time and does not cope with sudden or extreme changes of volatility (in other words, it works in Taleb's so-called mediocristan world but not in an extremistan world). Over time, people forget about such an assumption and limitation, the outcome gets taken for granted but could be off when the assumption is not met.

Besley and Hennesy (2010), on behalf of the British Academy Forum propose in their 'Financial and economic horizon-scanning: developing an early warning capacity', raising several issues to improve preparedness to economic shocks like caused by the recent financial crisis. They refer to economies that are inevitably unstable, to the genuine uncertainties of the financial and economic system which cannot be quantified, and to the challenge to understand discontinuities. An open mind needs to be encouraged to try anticipating what economic and financial shocks may occur in future. Besley and Hennesy (2010, p.13) call for 'an environment which provides sufficient criticism of assumptions and is open to considering a wide range of possibilities' and show how difficult this is to achieve: 'The hierarchical structures and histories of our many organisations provide a major challenge to making this work effectively. It was even suggested that there should be a rule that allows nobody to work in a particular position of responsibility for more than eight years.'

To summarize, economic crises are rarely predicted, the models in use fail to forecast sudden changes and disruptive events in the economy. There must be something missing in the models, the assumptions or the data. Model assumptions are still overly simple and remote from reality, but continue to be used. The models' reliability is at stake. Although dynamics and behavior has been incorporated in economics, hardly any economists foresaw the latest financial and economic crises. Something has to change.

3.8 Improving economic modelling through recognizing complexity

In the last decades alternative views in economic thinking have attempted to better deal with dynamics and the behaviour of single agents. Actually going back hundreds of years, Smith already wrote on the complexity in the social sciences representing one of the earliest and most cohesive discussions of the topic. Later, Schumpeter recognized the characteristics of innovation and change in the economic flow, causing spontaneous change, discontinuities and disturbance of equilibrium. He defined economic development through creative destruction. The entrepreneur has incentives to innovate causing the economy to be dynamic and disturbing the equilibrium state.

Hayek (1945, 1967) presented early ideas of economic thinking in evolutionary systems, though at that time it was limited to mapping biology models onto the economy. In his development of arguments he anticipated many of the key themes of complexity economics. Although he emphasized the importance of equilibrium, he expressed doubts on the linear mathematics and he came up with alternative models introducing complexity economics. At that time, computer power to experiment with the theory was limited; complexity needs computational modelling to analyze the complex interaction of agents and their environment. Hayek argued that in practical terms, it was impossible for any central planner to acquire all information needed to calculate correct prices; there is a knowledge coordination problem as all knowledge lies scattered all over society. Deductive rationality is simply not up to the job of understanding, predicting and planning in a system as non-linear and dynamic as the economy. Hayek (1945, p.519) famously wrote 'the "data" from which the economic calculus starts, are never for the whole society "given" to a single mind which could work out the implications, and can never be so given'. Information is dispersed, incomplete, contradictory and possessed by all individuals, it is a problem of utilization of knowledge which is not given to anyone in its totality. You cannot take a picture of a complex system, only a movie. Hayek defined that 'a social system is complex if all information that is needed to describe the state of the system at any point in time cannot be collected at one point'.

Georgescu-Roegen (1986), trained by Schumpeter, was one of the first to look at evolutionary theory and physics for answers to the shortcomings of traditional economics and in 1971 published 'The entropy law and the economic process'. He noticed the contradiction between neoclassical economics and the physical energy characteristics of the economy. His take was that economic systems exist in the real physical world and therefore they must obey the same law of entropy as everything else in the universe does. If the universe cannot escape the second law, then neither can economics. Economic activity is fundamentally about order creation, and evolution is the mechanism by which that order is created. Schumpeter called this evolutionary process 'creative destruction' and highlighted the importance of risk-taking entrepreneurs to make this evolution work through contributing to the prosperity of a society. Georgescu-Roegen's alternative view and criticisms were never seriously answered by the economic establishment, see Georgescu-Roegen (1997). It was Prigogine and Stengers (1997) who delivered the insight that the evolutionary process in biological and sociological systems does not lead to chaos; rather it adds value resulting in higher level of organization. They refer to the arrow of time and the constructive role of irreversible processes through which nature achieves complex structures and structure, only being possible in a non-equilibrium universe. Clearly the economy is not as a closed equilibrium system, but an open system that is not moving to equilibrium but actually chaotic and drifting away from a stable state; more specifically, it behaves as a complex adaptive system. If it were a closed system, then there would be a trend towards lower order of complexity and structure over time.

In the mid-eighties, a famous meeting took place in Santa Fe, in the US. Top scientists (both economists and physicists) exchanged ideas on major questions of life and discussed concepts of adaptation and emergence. They established complexity as a new branch of economic thinking, approaching challenges in society in a holistic way, based on the interaction of independent agents who adapt to each other and to their environment, from which new dynamics emerge. This goes beyond the old reductionist approach. Complexity in economics does not assume tendency to equilibrium in the marketplace, it rather assumes self-organization more or less following the mechanisms of evolution and may cause the economy to move in a zone between stability and turbulence, called the edge of (order and) chaos. Most of the initial theories are postulated by economist Arthur, one of the participants of the SFI meeting. The Santa Fe Institute (SFI) was born, studying complexity across all kinds of disciplines. Waldrop (1992), describes the formation of the SFI, the participants and their ideas, and states that particularly the diversity of people and ideas advanced the thinking about complexity much more rapidly than would otherwise be possible. The multidisciplinary approach of SFI is an asset to allow for broader scope. However, nowadays complexity economics is still not widespread and meets resistance from traditional economic thinkers.

The Organization for Economic Cooperation and Development (OECD) launched in 2015 an initiative called New Approaches to Economic Challenges, to renew and strengthen policy instruments and tools. They look in particular at complexity economics. The OECD (2015, p.3) states that 'The starkness and magnitude of the recent crisis and its lingering legacy calls for a serious reflection, to revisit and supplement existing policy approaches and build a new policy agenda for stronger, more resilient, inclusive and sustainable growth'. From debating the issue the OECD (2017, p.4) concludes that 'Economists and policy makers have failed to appreciate the complexity of human behavior and the systems in which we live. A complexity approach allows us to look at systems of systems consisting of vast numbers of individual elements that interact in complicated ways, such as ecosystems, financial markets, and energy networks, or societal phenomena such as urbanization and migration.'

In that meeting

- White (2016, p.5) dismisses the dominant thought of modelling the economy (using DSGE models) as a totally understandable and changeless machine. He calls for viewing the economy as a complex adaptive system, like a forest, with massive interdependencies among its parts and the potential for highly non-linear outcomes. A lesson learned is that crises are inevitable in a complex system, therefore: 'we must have ex ante mechanisms in place for managing them'. He finds that 'the trigger for a crisis is irrelevant, policy makers should focus on interdependencies and system risk and identify sign of potential instability building up and to react to them (e.g. built up of credit and debt levels). Complex systems can result in very large economic losses much more frequently than a normal distribution would suggest.
- Hoogduin (2016, p.11) calls for the 'modesty principle', being modest about what can be achieved with economic policy, as economic policy cannot deliver specific targets for economic growth, income distribution and inflation. This modesty principle also implies refraining from detailed economic forecasts as a basis for policymaking and execution. He states that 'societies and economies are complex systems, but the theories used to inform economic policies predominantly neglect complexity', and similarly humans have to deal with uncertainty rather than assumed risk.

- Beinhocker (2016, p.7) provides a concrete example how complexity could have helped policymakers: 'A team of researchers at Yale and several other universities have constructed a detailed bottom-up model of the housing market which shows the bubble in a new light. Unlike conventional top-down models, which show gentle self-correction, the team's 'agent-based model' showed the bubble bursting and markets crashing. The team modelled various policy responses to the housing bubble using real data. Conventional wisdom has been that sustained low interest rates following the 2000 dot-com crash were the primary cause of the housing bubble. But in the model raising the interest rates did not prevent a bubble forming, but tighter regulation of banks almost completely eradicated it.'

A number of people realize the financial market is complex but this insight has still not been sufficiently elaborated since. According to Rickards (2014, p.269) 'Complexity has not been warmly embraced by mainstream economics, in part because it reveals that much economic research for the past half-century is irrelevant or deeply flawed. Complexity is a quintessential example of new science overturning old scientific paradigms. Economists' failure to embrace the new science of complexity goes some way towards explaining why the market collapses in 1987, 1998, 2000, and 2008 were both unexpected and more severe than experts believed possible'. But as far as known, those working on complexity economics are not yet in a position to forecast crises; if they were it would have helped boost this approach among economists. At least complexity offers a way to understand the dynamics of feedback loops through recursive functions, it allows experimentation with modelling disruptive events and could prepare us for 'strange' outcomes. Better to be vaguely right than exactly wrong. In the next chapter we will look more into complexity economics, modelling and some results.

To conclude, a number of economists described improvements to economic modelling and acknowledged the economy being an evolutionary or complex system. Although complexity economics receives more attention in economic science lately, it is still not common and still meets resistance from traditional economic thinkers. Today's available computer processing power opens up better modelling possibilities for economic science, although compared to other sciences there is relatively little data available about the economic processes, except for financial transactions data.

3.9 Education

Much of what has been found as an answer to why we experience disruptive events as unexpected relate to how we think, what we assume and how we model. Here, education plays a very important role. If one wants to get better prepared for unexpected events, it is necessary to break out and challenge assumptions, models and the like and dare to look at alternative ways to avoid running in circles. It is challenging to have the formal educational system evolve at the same speed society is changing. Some put it quite firmly, like Hinssen (2014) when he claims society still has the old educational system from King Frederick William I of Prussia. With the goal of producing obedient workers for the mines, soldiers, well-subordinated civil servants to government, clerks in industry and citizens who thought alike about major issues. This would equalize the conditions of man.

It turns out that considerations described in this chapter are rarely embraced in the education system. Usually we start with only linear counting in primary school, and basic equilibrium seeking economic models teaching in secondary schools. Still little attention is paid to non-linearity, chaos and complexity thinking in higher economic education and the same holds for business schools. It looks like lessons from market crashes and booms lead to virtually no fundamental changes in the educational approach, while in the meantime most economists know the severe limitations of the traditional models. This lag obviously reinforces blind spots in thinking for future society, it is neglect of part of the outcome space. Insufficiently adapting the teaching materials, assumptions and models would leave us unprepared and again being surprised by the next rare event. We risk spreading misassumptions through education which strengthens the continuation of errors. It would be wise to spend more attention to complexity economics, and more generally, to the application of power laws, exponentials and non-linear behaviour of systems. If illustrated with practical examples teaching power laws and other non-linear behavior could even start in primary schools, when the mind is very open to new approaches.

Permanent education is important to basically everybody and holds in particular for teachers as they teach the next generation who deserve to learn new and alternative models. Even if they go with higher uncertainty or use a less stylistic math. Computational modelling could be supportive and fun at school, and allows experiments to watch alternative system behavior and study effects of changing assumptions. Methodological improvement could be made by better utilizing information technology in education. On-line learning delivers different and situationally better learning experience than class lessons, for instance as it could accelerate learning through direct feedback, and could help a teacher to show a broader variety of views on a certain problem or solution. Thanks to the ubiquitous availability of telecommunications, universities can now reach a wider public more easily through Massive Open Online Courses (MOOCs). Also other on-line education offerings (such as Udacity, Kahn Academy and channels like TED talks) could contribute to spreading alternative views to a potentially broad public. It is yet unclear whether these alternatives deliver better education, at least they allow for reaching a wider public and spreading alternative views easier and at low cost.

It is clear education plays a pivotal role in improving our preparedness for disruptive events, in particular by broadening the scope to a wider variety of models and techniques, to build up experience with non-linear and chaotic behavior of the economy.

3.10 Conclusions

A multitude of possible answers has been provided in an effort to explain why people often experience disruptive events as unexpected. These answers cover both things we do not expect as we simply never thought about them, and things we have been thinking about, for which we accepted the risk, but then neglected or forgot it.

It turns out our brain seems to prefer a quick answer based on heuristics rather than a well-calculated accurate answer. A consequence is that we wrongly estimate long-term risks. The human brain seems to prefer handling averages and normal distributions. We have a hard time imagining the consequence of exponential or power law functions, and consequently misjudge low probability high impact events. If such shortcomings on individual level are recognized, we could use structures or methods to protect society from such shortcomings.

However on the level of economic forecasting and policy we use economic models that suffer from other significant shortcomings. Important risk models do not help warn us of the biggest risk of all, as they don't work for the exceptional situations with very small probability and very high impact. Besides risk, people have difficulty dealing with uncertainty. We would rather use simple numbers and easy math than deal with uncertain outcomes, also as we fear losing face with communicating uncertainty. Economic models still often work with unrealistic assumptions on equilibrium seeking of markets, linearity, and using averages and normal distributions. As a consequence such models are no help in more difficult situations and have rarely forecast an economic crisis. Education using such models reinforces the continuation of mindset.

We clearly need other tools to cover the whole spectrum of probability, the unlikely events, as they cause big changes in economy and society. Complexity economics has been recognized as a promising road, though is still not common and needs to receive more attention and less resistance from traditional economic thinking. However, since the last crisis leading policymakers are astonished their models did not warn them, and now there seems more interest in renewing models using from complexity theory. It is key that we urgently update education programs too. Teaching non-linear behavior, power laws and complexity should start at an early age so avoid deepening a linear bias , allowing experimentation with non-linear models and chaotic system behavior.

The philosopher Hume said ‘It is not reason which is the guide of life, but custom’. Too often we extrapolate the past, keep doing what we have always done. As argued in this chapter, we risk continuing being oblivious to the fat tails and phase transition, and being surprised by the next unexpected event.

4 Suggestions to improve preparedness for unexpected events

We saw that the world is becoming more complex and by that unpredictable, driven by the growing influence of new technologies in our daily lives. These technologies are mostly network-based IT services that show exponentially curved growth. Both the network features and the exponential growth of computer capacity add more complex behavior to our systems. We also saw people have a hard time dealing with non-linearities and disruptions. Economic models dominantly in use cannot deal with non-linearities and chaotic behavior, and assume tendency to an equilibrium situation as output. However, there are clear signs that the economy acts like a complex system which would clarify disruptive moments and non-equilibrium seeking dynamics.

This chapter discusses three types of suggestions to better deal with complex behavior in order to get better prepared for the unexpected. First, complexity theory seems to be a much better fit to describe the interactions in our economy, tending more to the edge of chaos rather than seeking a state of equilibrium. It starts with an explanation of complex adaptive systems, showing the main characteristics and consequences, followed by further support of complex behavior of the economy. Next, examples of models of complex adaptive systems are provided. Second, further suggestions to better deal with complex behavior are focused on improving system design and resilience, looking at natural systems that are evolutionarily robust to absorb sudden events without the destabilizing the system. Third, suggestions are provided to improve education, to give complexity a more prominent place in economics. Let us return to the definition of complex systems and look at the main characteristics.

4.1 Complex adaptive systems

A complex system is defined as a system in which large networks of components with no central control and simple rules of operation give rise to complex collective behavior, sophisticated information processing and adaptation via learning or evolution, see Mitchell (2009). It models the behavior of agents, individuals and their interactions. One could differentiate between complex adaptive systems and non-adaptive systems, although most complex systems are adaptive. Adaptions means the systems change their behavior to improve their chances of survival or success through learning or evolutionary process. Reductionism doesn't work for complex systems. Reductionism has been dominant for many centuries with the idea to divide the difficulties under examination into parts, to understand the parts and the whole is the sum of the parts. However Einstein's relativity and quantum mechanics changed the world and marked the end of a reductionist era. The whole could be more than the sum of its parts, also called antireductionism. Physicists use complexity to explain the very small (quantum mechanics) and very large phenomena in the world (galaxies), however complex phenomena close to the human scale, such as human behavior, remain rather unexplained.

Complex systems are related to chaos theory, both are a branch of mathematics. Lorentz (1963) is considered as the founder of chaos theory, which looks at dynamic systems that are highly sensitive to initial conditions. Chaotic systems are deterministic, show randomness, but also underlying patterns, repetition and self-organization. Lorentz is famous for the insight of 'butterfly effect', which describes how a small change in an initial condition (the flap of a butterfly's wings in Brazil) can result in a large difference in a next state (set off a tornado in Texas), which obviously forms a big challenge to predict system behavior. Lorentz is particularly known for the so-called 'strange attractor'. An attractor is a virtual point, a state or a range of states where a system stabilizes, irrespective of a wide range of initial conditions in the system. A strange attractor typically occurs in chaotic systems when initial conditions of a process are very close to one another but after several iterations a path around two (or more) points arises, for instance in the shape of an eight. So, such a system is sensitive to the initial condition, a local instability, but shows a globally stable, complex outcome. Attractors play an important role in the emergence of order in a system. A main question in understanding a system (chaotic, complex) is to know what the attractors are. The properties of chaotic systems can be found in complex system behavior. However complex systems have a broader definition, they have more degrees of freedom, have elements that are only partly independent. They both deal with the dynamics of the parameters, but complexity also with the dynamics and structure of the system itself, and how it interacts with its environment.

We call systems like brains, insect colonies, cells, the immune system, the global economy and biological evolution, complex and adaptive. The question is how those systems in nature produce such complex and adaptive behavior from underlying simple rules. Despite the simple rules, the behavior of a group of actors, agents, becomes complex because of adaptation, which as we saw is influenced by preferential attachment. Agents organize themselves from which new, higher order patterns or behavior emerges. Such higher order structures and behavior have new and different properties that emerge from the lower level interaction and the self-organization. Emergence has been nicely framed by Holland (1998) with 'The hallmark of emergence is the sense of much coming from little.' In complex adaptive systems agents adapt to one another but also to higher structure and to the environment. Evolutionary behavior arises when the system creates possibilities of which some are chosen and further developed. Barabasi and Bonabeau (2003) show how various complex systems have an underlying scale-free network that evolves through preferential attachment, thus not at random, having implications for its robustness. Bak (1996) refers to self-organized criticality being the foundation for catastrophism. There is a tendency for large systems to evolve into a critical state, out of balance and sensitive to avalanches. Most of the changes take place through catastrophic events rather than by following a smooth gradual path. Real-life operates at a critical point between order and chaos. Although complex adaptive systems may show stability, they are not in control and are not perfect. They are most stable when variety and diversity are present.They could end in equilibrium, but mostly do not and evolve in coevolution, on the edge of chaos and away from equilibrium. Typically large fluctuations cannot be prevented by local adjustments and any small behavior in the critical state of a complex system will eventually affect everything in the system.

There is neither a single science of complexity nor a single complexity theory yet. There are many ways proposed for how we could measure complexity, but no universally accepted way has been agreed by scientists yet. Mitchell (2009) describes several possibilities for measuring complexity, such as thermodynamics, fractal dimensions and hierarchy.

A main question is how to compute or predict the outcome of complex behavior. You can use models to simulate the behavior of agents, use probabilities and distributions. When more and more information is obtained, concepts get recognized and dominant patterns arise which makes the outcome more deterministic. But deterministic does not mean predictable. Chaotic systems are deterministic, i.e. no randomness in the process so their behaviour is determined by the initial condition, but these systems are sensitive to small changes in initial conditions and therefore show unpredictable behaviour. Like the weather, a small distortion may lead to a major change. Complex systems, with even more degrees of freedom and dynamic structures, cause their own unpredictability and are inherently beyond control. There are at present limitations to the predictability of complexity models, as Bak (1996, p.9) said ‘at most, the theory can explain why there is variability, or what typical patterns may emerge, not what the particular outcome of a particular system will be’. Timing is hard and the consequences of triggers may vary.

A prediction is a statement about an uncertain event, often based on knowledge or experience. Prediction is often what we are looking for, in particular since we have so much data, but it is far from obvious because of complex behavior. Kelly (1956) revealed the deeper patterns about the nature of prediction for a type of gambling, known as the Kelly criterion. He described the mathematics for the case of having an information or statistical edge and how to maximize benefits from asymmetries in information and statistics. The power of the Kelly criterion is the fact it is a simple formula which forms a heuristic in a situation of uncertainty, however the use of this criterion is limited to some systems. The human success of prediction is quite limited: the biggest discoveries in the world were not predicted. Larremore and Clauset (2017) suggest that we do not see big discoveries coming just because they reorganize how we thought the world worked, they view big discoveries as valuable precisely because they are fresh and new whereas predictions are based on historical patterns. They also state that in the age of bigger data and better algorithms, researchers are discovering straightforward systems that appear to be fundamentally unpredictable, as well as complicated systems whose behavior is surprisingly predictable.

Finding the organizing patterns and at the same time challenging the limits to prediction are at the core of complex systems research. Miller and Page (2007) clarify that complexity can produce predictions. Although any outcome of the model differs from others as the rules contain random features, a large set of outcomes produces a distribution of outcomes providing an indication of a real-world, behavioral driven, outcomes distribution. Such distribution outcomes are more accurate than the precise looking numbers from traditional models, but probably perceived as harder to deal with in policymaking requiring learning and changing habits. It is difficult though for the human brain to deal with complexity. Complexity models such as agent-base models, could be used to identify signals of growing instability, for instance a steep growth of debt, and model what reaction would be best. They could deliver policymakers the insight that a small increase of a high debt level could just be too much and makes the complex system chaotically moving into a different phase. Policymakers could use such models to reduce outcomes of economic instability.

4.2 The economy as an evolutionary complex system

Complexity theory could be used to explain the dynamics of the economy and the financial system. The dynamic behavior in the economy is widely recognized as being complex as shown in the former chapter, but complexity is still not widely applied and deserves much more attention to provide better insights in economic behavior, to improve economic (financial) systems and to develop early warning systems.

Limited rationality in behavior of individual agents has been recognized by economists. Simon (1957) viewed agents as bounded-rational agents, as rationality is limited by the information and time available, as well as (willingness) to process all available information. So individual agents often act rationally within their scope of possibilities. The higher order patterns that could emerge show (a perceived) irrational outcome or politically unwanted outcome. Recognizing the interconnectedness and adaptive characteristics of agents, the emergent order that arises from individual agent behavior and network effects like path dependency of events are key to improving our understanding of developments that may lead to sudden events. Typically network dynamics lead to self-organized criticality which behaves at the edge of chaos and may lead to some major shift, crisis or phase transitions. For example Gladwell (2000) shows changes do not happen gradually in society, rather radically, like the fall of crime in a city. The change propagated like a virus, a few little causes lead to big effects, fast, radically and dependent of context. Inherently to complex systems small changes may lead to totally different outcomes as passing a tipping point causes the small feature to break through and becoming dominant. Collective behavior in society clearly does not follow a linear path. Another complex system effect in the economy, not grasped by mainstream models, is the dependency of history. Gladwell (2008) views outliers in society as successful partly by hard work (the famous 'you need at least 10,000 hours of practice') but also cultural legacy is of importance. Success partly arises out of the steady accumulation of advantages, like when and where you were born, what your parents did for a living and what the circumstances of your upbringing were, all make a significant difference in how well you do in the world. So the path followed is relevant, in other words history matters. Path dependency is a positive feedback mechanism in the network and clarifies many higher order patterns in the economy. Complexity models fit such progression, whereas mainstream models miss such dynamics and may produce wrong conclusions.

The complexity of human behavior causes the economy to behave as a complex system. We see copying behavior by individuals, resulting in positive feedback loops triggering herd behavior, and groups of people acting together from which self-organized behavior emerges. Economic growth is an emergent property. Beinhocker (2006) explains 'trades happen bottom-up and are self-organized, there is no full control over the whole chain of trade; there is no one in charge of the global economy.' As explained earlier there is no central control in a complex adaptive system. The effect of attempts to control are rather uncertain as the complex behaving system will react in a complex way to the (external) change which is not rather well understood and depends very much on the (critical) phase it behaves. Beinhocker states that our rationality and creativity feed and shape the workings of the evolutionary algorithm in the economy, but do not replace it. The evolution discovers designs, through a process of trial and error. A variety of candidate designs are created and tried out in the environment; designs that are successful are retained, replicated and build on (the amplification), while those designs that are unsuccessful are discarded. It is the way how (small) businesses usually work with prototyping and quickly improving and trying. Beinhocker (2006, p.15) says: 'Despite all the strength and virtues of human rationality, prediction in a system as complex as the economy over anything but the very short-term is next to impossible'. All we can do is to build in more resilience in the system and to recognize and identify signals of distortion.

Beinhocker (2006) sees the economy as an evolutionary complex adaptive system. He sees evolution as an algorithm, not just biological, rather an all-purpose formula for innovation, it creates new designs through trial and error and solves difficult problems. This process consists of three steps: differentiation, selection and amplifications, which together according to Beinhocker form the process of economic wealth creation. His idea that the economy is an evolutionary system is a radical idea and contradicts with standard economic theory from the past century, however it is not new. It seems that Darwin was inspired by economist Malthus for his theory on the formation of new species, which then influenced economic thinking in evolutionary systems by Schumpeter, Hayek, Nelson and Winter. However it had too little impact and traditional thinking around economic equilibria remained. Dennett (1995) called evolution a general-purpose algorithm for creating 'design without a designer'. Evolution would be information processing, it creates order in computer software, in the mind, in human culture and in the economy. Assume that both economic and biological systems are subclasses of a more general and universal class of evolutionary systems. Evolution consists of a powerful three step formula of differentiate ideas, select, amplify the best one(s) and reiterate. The vital ingredients of 'survival of the fittest' are adaptation and cooperation. These characteristics can be applied ubiquitously to the survival of an idea, organization or economy, so evolution can be seen as the algorithm that can reliably and quickly find good designs in an enormous design space, be it in biology, economy or technology.

In the economic evolution, Beinhocker (2006) identifies three sub-processes: the development of 1) physical technology, such as tools, machines, chips, software; 2) social technologies, i.e. ways to organize people to do things, such as the assembly line, and which impacts our interactions and changes the way we used to live; and 3) business models, which turn physical and social technologies from concept into reality, via products and services. He sees business designs as evolving over time through a process of differentiation, selection and amplification, with the market as the ultimate arbiter of fitness and technology often changing the business model and creating different business opportunities. From this evolutionary point of view, one sees that companies have an interest to not only focus on growth and profit, but also on endurance. Adaptability is important to remain relevant and to survive, though experimenting with and investing in new and risky technologies could be challenging if that would cannibalize own cash cows (as we saw in the Kodak example before). This idea is in line with Christensen (1997), who clarifies that boards risk not seeing the future importance of a new development, and if an idea is perceived as less important it won't get the resources; whereas assigning resources to promising technologies could continue near future cash flow. The evolutionary approach puts more emphasis on continuity and endurance, and sees profit as a support to these goals, in the interest of all stakeholders including the shareholders.

As the evolutionary complex economy works without central control, Beinhocker (2006, p.214) emphasizes the endogenous part of evolution, as it is not assisted by an outside designer or programmer. He views the evolutionary process of technologies as a process of 'sifting from an enormous space of possibilities', with errors creating copies not quite identical, with good replicators get replicated and evolution ultimately selects for building blocks that support replication, supporting their own replication (i.e. 'selfish', compare with Dawkins' selfish gene). From this perspective a virus is a replicating disruptor. Information processing is key in this evolution and communication of humans, i.e. spoken and written language, amplified information processing has speeded up this evolution process. The evolution algorithm creates order from randomness. 'From simple random beginnings, the algorithm creates complex designs that are 'ordered' from the point of view of the fitness function. All evolutionary processes operate in open systems, so in effect the algorithm harnesses energy to decrease local entropy and turn randomness into order'.

A consequence of no central control is the limited use of attempts to centrally steer the economy or financial system. The political focus on GDP growth and the central bank's focus on targeting a certain level of inflation are at least immodest in a system context of no central control. Rickards (2014) sees the central bank top-down approach being in contradiction with complexity theory and warns inflation targets fit equilibrium thinking which neglects the positive feedback loop that emerges, which leads to even higher inflation. Along the same lines, Hoogduin (2016, p.11) argues the need to recognize the complexity of the economy and the fact that agents do not face risk about the future rather uncertainty which is by definition unpredictable. As a consequence he argues that 'economic policy makers would be wise to stop pretending that they can deliver what they cannot. This insight implies that many current policies should be discontinued.

To mention just one example: inflation targeting by central banks does not pass the modesty test. This principle also implies refraining from detailed economic forecasts as a basis for policy making and execution'.

Summarized, it is likely that the economy is as an evolutionary complex adaptive system. The three-way coevolution of physical technologies, social technologies and business designs account for the patterns of change and growth we see in the economy, following an evolutionary process of differentiation, selection and amplifications. The adaptability in the system is key to surviving this evolutionary process. The evolutionary complexity approach helps us to model the selection and adaption mechanisms in the real economy and clarifies why those who do not adapt, get disrupted. The approach leaves no room for central control.

4.3 Examples of models of complex adaptive systems

One of the earlier models known for accepting chaotic outcomes is the cobweb model. It acknowledges that lack of perfect information and adapting expectations can lead to instable outcomes, though one can question whether it models a complex adaptive system. The cobweb model describes supply and demand that periodically fluctuate, like in agriculture markets, when price and amount produced are set at different moments in time. The outcome of the model shows a web of demand and supply fluctuations, which could convergence to equilibrium but also diverge to chaotic price fluctuations. Hommes (1994) investigates a non-linear cobweb model with adaptive expectations (an S-shape supply curve) and proved chaotic price dynamics occur generically, showing chaos may occur under simple and reasonable economic assumptions.

Agent-Based Modelling (ABM) is probably the most known and used way to model emergent behavior in a complex system. ABM is a class of computational models composed of a (large) set of heterogeneous agents, with their own goals and behaviors, which can any moment react to each other and to the environment. The agents can learn and adapt their behavior according to certain decision-making rules. For example, agents could be banks, consumers, producers and governments, who all react to each other and to the outcome those agents together create. One can test forecasts, strategies and actions for survival within a certain set-up. From the agents' interactions economic occurrences emerge. One could experiment with initial settings to study stability and desirability of outcomes. ABM are scalable, dynamic, process oriented repeatable and low-cost. A well-known software example for agent-based modelling is NetLogo, developed by Wilensky at Northwestern University.

ABM certainly does not assume tendency towards an equilibrium, like mainstream economics does, it actually starts to assume non-equilibrium as the natural state. This way you can cope with the fundamental uncertainties (Knight; Keynes) of agents that do not know what they face. Equilibrium may be the outcome of the model, and it may not be. Schelling's model of segregation from 1971 is probably one of the oldest agent-based models. He modelled social integration in neighborhoods through testing how to achieve the lowest number of unhappy people. The model shows adaptation of agents leads to more segregation and no stable equilibrium while the expectation was that equally spreading people would result in an equilibrium and robust social integration outcome.

A valuable introduction to ABM, the objectives and set-up is provided by Miller and Page (2007). They discuss the Forest Fire model, an interesting implementation of an ABM showing the dynamics of agents' behavior to reach an optimal macro outcome to protect a forest, see explanation in section 2.4. A number of other models for complex adaptive social systems are described, as well as practices that promote quality science in computational modelling. The main other models are:

- Cellular automata: each agent's behavior is driven by the same generic rule.
- Social Cellular automata: accept the notion that all agents employ a common, fixed rule; socially acceptable behavioral rules; outcome symmetry; rules looking at local copy behavior.
- Majority rule model: assume that agents attempt to take actions that are consistent with the majority of their neighbors. Could be deterministic, or have random elements to capture features such as mistakes, experimentation, and tendency to bias choices imperfectly.
- Models to deal with the "Edge of chaos": systems at the edge of chaos have the capacity for emergent computation. Systems that are too simple are static and those that are too active are chaotic, and thus it is only at the edge between these two behaviors where a system can undertake productive activity. If we attempt to incorporate more delicate behavior by adding more structure to a rule, we are likely to make the underlying system less robust. Because the structures necessary for delicate behavior require an underlying system that is rich in possibilities, it need to fall into the right state with only a gentle tap and could lead to unpredictable results. The edge of chaos captures the essence of all interesting adaptive systems as they evolve to this boundary between stable order and unstable chaos.

Let us look at a number of examples of agent-based models. A famous application of agent-based modelling is the 'Santa Fe artificial stock market'. It is an agent-based market that generates several features resembling actual financial data and investors' choices, and allows a financial market to be built with several trading strategies. Like an evolutionary mechanism, successful strategies remain and gain influence, weak strategies could disappear and new strategies could appear. The model captures the unpredictability of stock markets, it does not assume fully rational investors, nor perfect efficient markets. The earlier version of the market is described by Palmer et al. (1994), key results of this version and further developed ones can be found in Arthur et al. (1997), while LeBaron (2002) describes the design questions that went into building the market.

Simon (1996) discusses various tools for analyzing complexity. He looks at artificial systems in various disciplines, in search of understanding the natural and artificial (man-made) world and investigates the implications of artificiality for complexity. He also looks at the importance of hierarchy in complex systems and shows how complex systems evolve from simple to complex more rapidly through intermediate forms, causing hierarchical complex systems. Looking at the behavior of an agent, Simon (1957) explained in earlier work that agents make bounded-rational decisions. They cannot act fully rationally because of uncertainty and cost of information, they use limited information and look at satisfactory rather than optimal payoffs. This is line with Kahneman's heuristics and biases as described before.

A variety of complexity modelling has been performed on financial systems, studying the interaction of large numbers of interacting agents with heterogeneous goals and behavior. LeBaron (2000) analyzed the results of a number of studies and finds that these studies reveal very different perspectives on traditional theoretical thinking and provide new, important and very different approaches to mainstream economic modeling. The following studies are analyzed by him: one that deals with evolution and learning in a population of traders; another with trading experiments seeking the amount of 'intelligence' necessary to generate the results they were seeing; one on a simulation of more complicated foreign exchange market structures; another that focuses on ideas of uncertainty and information in financial markets; then the Santa Fe artificial stock market experiment and finally one on a neural network based market structure where agents trading takes place in a random matching environment.

Further on heterogeneity, Hommes (2006) reviews a number of dynamic heterogeneous agent-based models that describe financial markets as a complex system. Agents are assumed to be bounded-rational agents as defined by Simon (1957). Heterogeneous agents use different decision processes, and a decision by one agent impacts the others who learns dynamically or through forward looking. These models include non-linear, chaotic and evolutionary features and can be used to explain important dynamics in financial markets, such as 'excess volatility, high trading volume, temporary bubbles and trend following, sudden crashes and mean reversion, clustered volatility and fat tails in the returns distribution' (p.2).

A further example is shown by Van den End (2017), who applies complexity theory to interest rates. Complexity helps to illustrate that accelerating dynamics in a financial system with too much liquidity could face a critical transitions to a new state, a bifurcation, caused by the excess liquidity. At some level of excess liquidity the system can become unstable and shift to a new stable state. It may well be just a small, even unexpected, trigger that drives the system into the critical transition, followed by a positive feedback looping bringing the system to a new (stable) state. He concludes with 'The complexity approach provides central banks a new framework to assess the (unintended) consequences of their interventions in financial markets' (p.26).

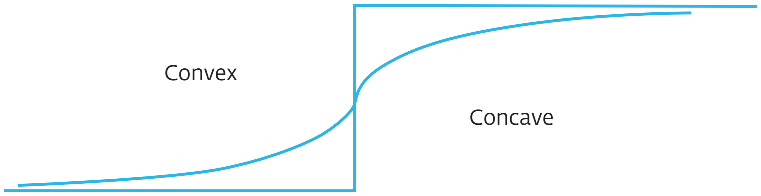
The various examples of computational modelling show a variety of possibilities for analyzing the complex dynamics of systems, and they indicate how changes in parameters could lead to non-linear and sometimes disruptive changes in system behavior. The area is still in development, but it

128 provides promising alternative views necessary to get better prepared for disruptive events. In order to better understand the systems we use as well as to better understand the impact of (small) changes we make to our systems, computational modelling should be used more often.

4.4 Resilience, diversity and the opposite of fragility

Taleb (2012) shows that adding robustness (redundancies, buffers) to a system is not enough, or is simply not the answer. He argues the goal should be to make a system or network the opposite of fragile, namely antifragile which means it becomes stronger when it is kicked (like our immune system). Antifragility is beyond resilience or robustness; the resilient resists shocks and stays the same whereas the antifragile gets better. It is like hormesis: a small dose of harmful substance is actually beneficial for the organism and acts as medicine. Thanks to the small dose of toxin, the body can resist higher levels of toxicity and so becomes stronger. Similar with vaccination, injecting a little illness to activate the immune system to get prepared for a much tougher invasion of the same illness. Examples by Taleb of systems having this feature are: evolution, culture, ideas, revolution, political systems, technical innovation, recipes and bacterial resistance. Antifragile loves randomness and uncertainty, and even errors. It benefits from uncertainty and chaos. Antifragility allows us to deal with the unknown, to do things without understanding them and do them well. Taleb reasons that we are better at doing than at thinking so you are better off being dumb and antifragile than extremely smart and fragile. He continues that (anti)fragility is easy to detect by using a simple test of asymmetry: anything that has more upside than downside from random events (or certain shocks) is antifragile; and the reverse is fragile. To stay on the safe side we need to respect variety, and limit the dose of anything to about half of its maximum. That means on an S-curve of growth one should stay on the convex part (the left side) to remain antifragile, as the concave part represents (a move to) fragility; see chart 4.1. It represents something

Chart 4.1 A convex-concave diagram: growth from left to right, from antifragile to fragile



Source: Taleb.

with monotone growth and bounded, e.g. a dose, or wealth, anything. From left to right something becomes gradually more effective, but further to the right the dose becomes ineffective and may hurt, i.e. the system becomes fragile.

In practice, many man-created systems have become very much fragile as the focus shifts towards short-term interference. Taleb (2012, p.10) warns to 'engage in policies and actions, all artificial, in which the benefits are small and visible, and the side effects potentially severe and invisible'. As examples he mentions doctors who tend to deny the body's natural ability to heal and give medications with potentially very severe (long-term) side effects; economists who mistake the economy for a machine that continuously needs fixing; and financial specialists who make people use risk models that destroy the banking systems. Taleb says the blindness to fragility is caused by selective memory and absence of skin in the game, as those who have skin in the game prefer simplicity over complexity, and operate more fluidly following own convictions. The same holds for flexibility over precision. Precise models and precise preconditions, using detailed mathematical techniques, often lack flexibility in the phenomena that we can explore, whereas computation models represent an interesting trade-off between flexibility and precision. However, the simplicity of heuristics may neglect the rare events as well, which actually causes a problem. There is a big risk that, while seeking efficiency, we build more and more systems vulnerable to black swans, of which the odds are not computable. The rarer the event, the less tractable and the less we know about how frequent its occurrence. We have to take into account that people underestimate randomness and underestimate (long-term) harm.

Haldane (2009) addresses the emergence of two characteristics of the financial network, i.e. complexity and homogeneity. He finds that these characteristics make a financial network 1) both robust and fragile, a property exhibited by other complex adaptive networks; 2) whose feedback under stress actually adds to the fragilities through a positive feedback loop; 3) the emergent behavior amplifies uncertainty in the pricing of assets; 4) innovation increases further network dimensionality, complexity and uncertainty; and 5) diversity has eroded lowering the resilience of the system. Robust and fragile could apply to the same system, namely robust when still on the convex side where the network can afford losing a few randomly selected vertices and fragile when at the concave side where the network could fall apart when losing a few of the largest vertices. Haldane provides three explanations for the robust and fragile property of interconnected networks. First, these networks have a tipping point property. In the range before that point, connections offer alternatives and diversity, so absorb shocks and provide overall robustness, however beyond that tipping point fragility increases when connections serve as shock propagators. Second, he refers to others who found that the longer-tailed distribution feature of many complex systems (like internet, food webs and payments systems) seem to make them more robust to random disturbances compared to normal distributed systems, but more vulnerable to targeted attacks. Third, he concludes that the small-world property, known from the six steps chain letter experiment by Milgram in 1967, could be an explanation that local disturbances in interconnected networks quickly have a global reach. This would clarify why relatively small disturbances of banks in some smaller European countries caused such a wide-reaching disturbance in the financial network. Similarly a local cyber-attack could have far reaching implications because they propagate fast through a network lacking diversity and variety. Recall that from the general characteristics of complex systems typically large fluctuations cannot be prevented by local adjustments and any small behavior in the critical state of a complex system will eventually affects everything in the system.

If one takes the complexity characteristic as a given, the solutions for keeping the financial network resilient is in staying well before that tipping point, that is the area with diversity among the players. Policies should focus on retaining diversity and incentivize creating more diversity among actors to counter a trend towards homogeneity. If indeed homogeneity is a characteristic of the financial network, one could conclude that this is a design error as it increases fragility and lowers resilience. This conclusion would fit the outcome of the forest fire model in which homogeneity led to a critical situation whereas heterogeneously adapting agents made the system less fragile (and even led to higher productivity of the system). The opposite actually happened to the financial system, the diversity and variety has diminished lately causing risk to (the longer-term) continuity and resilience of the system. As we saw, Taleb (2012) calls for systems that actually improve from disturbance, like the human immune system, which is a good example of adaptability. Evolution and discovery can handle disturbance and tend to get better, they have a high degree of adaptive capacity. He views the present policies with bailouts and assumed statism not only makes the system weaker, but it blocks economic evolution and prevents this mechanism from letting the economy become stronger and less fragile.

The concept of anti-fragility is a motivation to have a fresh look at financial stability. The challenge is to design an antifragile financial system, or add antifragility features to the system, in order it to handle what Taleb (2012, p.13) calls the 'extended 'disorder family': uncertainty, variability, imperfectness, incompleteness of knowledge, chance, chaos, volatility, disorder, entropy, time, the unknown, randomness, turmoil, stressor, error, dispersion of outcomes and un-knowledge'. We saw that these characteristics fit (natural) evolutionary complex adaptive systems and an artificial (financial) system should be designed following the characteristics of such complex systems as discussed earlier. Consequences for the present system would be: diversity among vertices and rich in possibilities, no vertices 'too big to fail', skin in the game, simple rules for agents and vertices and an immune system to make the whole system antifragile.

When discussing systems at the edge of chaos, Miller and Page (2007, p.139) question the edge of robustness. Their modelling shows that fine-tuning these systems creates a tension: 'As we attempt to incorporate more delicate behavior by adding more structure to a rule, we are likely to make the underlying system less robust. This is because the structures necessary for delicate behavior require an underlying system that is rich in possibilities. In essence, we need a quivering system that will fall into the right state with only a gentle tap. In such a system, an improper tap can lead to very unpredictable results. Adaptive systems have to deal with the tension between the benefits of achieving precise behavior and the cost of increased system fragility. One hypothesis is that adaptive systems will have a bias towards emphasizing simple structures that resist chaos over more complicated ones that handle difficult situations.'

In sum, every system that does not like volatility, does not like stressors, harm and chaos. Robust systems are neither harmed nor helped by volatility and disorder, while the antifragile would benefits from such disturbances. Diversity, limited size, simplicity and adaptability of actors or subsystems are key to keep the system resilient.

4.5 Suggestions for improving the financial system to handle complexity

The recent financial crisis shows that the interconnectedness of financial institutions led to uncertainty whether or not a threatened bank, i.e. a vertex in the network, could be missed in the networked system. From Perrow's (1999) 'normal accident' theory we learned that the combination of highly complex and too tightly coupled components causes the biggest risk of accidents in systems. Moreover, diversity and heterogeneity of actors and technology limits the vulnerability of becoming too tightly coupled. Perrow advises to either completely redesign systems that are too complex and too tightly coupled, or abandon them. Mezias (1994) analyzed the savings and loan crisis (S&L, US 1986-1995) and finds a fit with Perrow's theory. Mezias argues that the main causes of that crisis were not the commonly mentioned fraud, mismanagement and unusually high inflation rate, rather the very tight coupling between firms, auditors and the state. He argues the institution's offerings became increasingly the same and inadequate regulatory responses to the changing circumstances exacerbated the tight coupling. He argues that the institutional environment added tightness to the system. He views isomorphic pressure from regulation and the accounting profession made the firms more similar, and the huge jump in the ceiling of the deposit insurance made the government suddenly the big guarantor, which led to high risk taking across the whole S&L sector and to a tight coupling among all depositors. The tight coupling caused a cascade of failures. They all followed the same, wrong model. Mezias (1994, p.190) concludes 'Public policy must be designed to avoid catastrophic accidents. The way to do this is either to reduce the complexity of these systems or to reduce the tight coupling among constituent units of these systems'.

Well-designed networks are resilient to losing a few vertices. Networks with vertices that have a very high number of edges (a high degree) are the main spreaders in a network and removing one or a few of them has destructive effects on the whole network ('too big to fail'). From a network design perspective 'too big to fail' is a design error, and so are tight couplings. Such vertices cause uncertainty in society over the question whether indeed they will be rescued, they cause moral hazard and high cost to society for rescue and indirectly for uncertainty and loss of trust in the system. There must be private benefits, but for society benefits are limited, if existing, and turn into a huge cost transferred to others if it fails. Ten years after the recent financial crisis the problem has not been solved. It is not only the financial system that deals with players 'too big to fail', the issue has been at stake with private producers of telecommunications, energy and cars; and in the meantime we also have become dependent on private network platforms that dominate a sector be it search engines, retail or messaging platforms. For the private sector, 'too big to fail' should simply be avoided because the cost of failure to society is by definition too high. Therefore resilient networks should reasonably limit the degree of a vertex such that one or a few of them can be missed without destabilizing the whole network.

For public infrastructure one can argue that centralized solutions are beneficial to society as benefits from scale efficiencies are passed on to society in a fair manner while proper governance avoids excessive costs for society. However, inherent vulnerabilities of such centralized solutions remain, even when mitigated with proper business continuity measures such as alternative sites and secured access. Think about software bugs that affect all sites, cyber-attacks and hacks from within the organization.

Systemic risk in the financial system refers to risk of instability of the financial system, either caused by a failure in one of the financial market infrastructures or a bank failure that triggers further bank failures. Taking nature as example, to reduce systemic risk in the financial system would mean to design an infrastructure with a diversity of many institutions, limited in size, with optimal interconnectivity and some hierarchy. Optimal interconnectivity means institutions should not be coupled too tightly, nor should their environment be, as described by Mezias (1994). In a loosely coupled system, one or several bank failures would not lead to systemic risk but be absorbed by the system and resolution measures. Also the financial market infrastructures should have natural features that make it survive (an operational) failure, for instance by a decentralized set up using variety in implementation. Global services and efficiency benefits for customers can be achieved in such a network, global actors are not the only way to achieve such goal. The argument that big players are a necessity to offer global reach for large customers is one of efficiency for the actor, but cost for the system. Rickards (2014) proposes to break up large banks, so that bank failures are not a threat to the system anymore. They are not necessary for large financing, as a lead bank can organize a syndicate. It would not avoid bank failure, but bank failure would not pose a threat to the system anymore and its cost would not threaten society.

The argument of efficiency is true at some level, but creates cost at a higher level (system, society) in the longer term (monopolistic behavior, dependencies). Compare with the original set-up of the internet where there was no systemic problem if one or a few webservers went down; unfortunately also here our governance model has allowed for dominance by a few larger players that put the natural redundancy concept at risk. In contrast, today we try to deal with dominant players in our systems, be it banks, platforms, hospitals, schools or cities, and the dominancy seems to grow. The concept of evolutionary complex adaptive systems allows us to reconsider the present set-up of the systems based on centralized solutions and a few big players that have become ‘too big to fail’.

We need a mechanism to limit the size of a financial institution, in such a way that on system level we can afford a few ones to go into resolution or default. That means the natural mechanism of preferential attachment to a successful financial institution needs to be maximized (technically the power law growth would be bended off to some kind of S-curve). The financial system could become stronger from a default as it creates room for more diversity in players. It also creates room for new and potentially better ideas, from both new and existing players, which can be selected by them, and amplified through the evolutionary characteristic of the complex system.

We also need a mechanism to keep the rules simple, challenging the present legislative and governance framework, and for instance affecting supervision. There seems to be bureaucratic reflex to act, to intervene, with more rules and treatments rather than taking the opportunity to simplify and allow the system itself to heal. The system should be capable of experiencing several relative small painful events (illness, a fire, bank failure or cyber-attack), they are natural and allow the system to absorb, to correct and to remain robust and become antifragile as after the fire there is room for diversity and new players. According to such approach, badly managed banks or governments should fail in order to avoid a large unmanageable fire. For self-healing behavior Taleb (2012) refers to the medical phenomenon iatrogenesis, i.e. harm caused by the healer. Like harm to an individual undergoing treatment because some of the group gain from the treatment but the net loss from the treatment is in excess of the benefits; the damage is often hidden or delayed. Examples are bloodletting, unnecessary operations shortening life expectancy and antibiotics. Taleb (2012, p.113) puts it firmly as ‘anything in which there is naïve interventionism, nay even just intervention, will have iatrogenics’. Interventionism comes from the need to do something and depletes mental and economic resources. Part of the problem is the centralized control mechanism that prevents the evolutionary mechanism from healing the system. Examples of consequences of intervention in the financial system, although meant as healing, are moral hazard, wrong incentives to bank management, further borrowing beyond affordable levels, hollowing out savings and pensions, delayed restructuring of the financial system and of government budgets, loss of trust, more rules and increased costs of regulation.

An important mitigator of fragility is 'skin in the game'. Taleb (2012) states that an entrepreneur typically has skin in the game, a corporate executive does not. Citizens have, bureaucrats do not, and activists have, politicians do not. He makes us aware that most of the power is in the hands of those who do not have skin in the game. We see the transfer of fragility and antifragility from one party to the other with the power going to the ones without skin in the game. It looks like lack of courage. Mechanisms are necessary to incentivize 'skin in the game'.

There is also a need for better mechanisms to manage risk that arises from the increased interconnectedness. The technological development and increased connectedness have improved existing services, made them faster, less prone to errors and brought us new services. Financial services have dramatically improved with straight through processing and direct access to the account. But the widespread connectivity has also caused an increase of system risk because interruptions can faster propagate through a more interconnected network and infect other actors (e.g. cyber-attacks, liquidity risks). Society has also become more sensitive to attacks on stored data and the ubiquitously distribution of sensitive data, such as money transfer instructions, password updates, credit card data stored at web merchants, but also the distribution of false news. Surveillance, crime and terror can make use of similar possibilities through information technologies and already show the weaknesses in our information prone society. The impact of events is getting larger through the network, requiring mechanisms to protect the integrity of data as well as the continuity of service.

Concluding that capital markets are complex systems has profound implications for regulation and risk management because the power law function at systemic scale causes the risk to accelerate following the power law. Richards (2014, p.11) describes two implications: 1) 'stress tests based on historic episodes such as 9/11 or 2008 are of no value'; and 2) 'the proper measure of risk is the gross notional value of derivatives, not the net amount'. On the limited value of the stress tests based on historical data, imagine looking back at a power law curve to see a slowly increasing curve, while looking ahead on the same curve it goes steeply up, so one may expect risk to explode through the power law with the growth of the market. On his remark regarding risk measure, indeed the emerged behavior of settling net amounts becomes a new normal system behavior with large liquidity savings. However in a sudden, abnormal situation, if a few of the larger actors fail and cause the netting to fail, the other actors are left with much larger positions, potentially up to the sum of their gross positions. The gross notional value of derivatives is huge, a multiple of world GDP. According to the Bank for International Settlements (BIS), outstanding positions in over-the-counter derivatives markets in notional amounts outstanding reported by dealers, totaled USD 544 trillion at end-June 2016, of which 62% was centrally cleared. According to the World Bank the world GDP 2016 totaled USD 75 trillion. His point is that the non-linearity characteristic of the financial system is overlooked, derivatives increase the interconnectedness and systemic scale of the financial system and if the system size doubles risk would not double but increase much more due the power law characteristic. In sum, the risk of financial products need to be viewed in the context of the interconnected network and kept limited as risk follows a power law in a complex system.

It is important to acknowledge that complex problems not always require complex solutions. Simple solutions actually often tend to offer a robust answer. Heuristics can be seen as a tool to deal with complex situations, in particular with uncertainty, as described in chapter 3. Other tools are trial and error, follow the crowd and past is like future. Heuristics are useful, though we need to recognize when heuristics are actually an inaccurate but fast solution and when heuristics are a superior solution compared to other, complex, solutions. Shortcomings of heuristics are caused by a limited use of information in order to save time. Experimental evidence shows investors do not discount as assumed, they have biases regarding risk and have framing errors. Heuristics also leads to preoccupation, by negative news and exceptions, and consequently not being open to new data and methods but seeking confirmation of what is already known. These inaccuracies cause us to lose sight of the low probable, disruptive events. Heuristics may give us an illusion of control, believing we have control over chance events. Benefits of heuristics are that they are simple and easy to implement. People usually know that heuristics are not perfect, but it becomes dangerous when they forget.

Kahneman (2011) concludes that we need heuristics for decision making, because our brain has limited processing power and time, and simply does not know all data and probabilities. Taleb (2012) states heuristics being favorable over regulation, as legislators have a tendency to make complex regulation; insiders are the enemies of the ‘less is more rule’. Gigerenzer (2016) calls for studies that deal with uncertainty systematically and sees heuristics as a way to deal with uncertainty systematically. He says good decisions under risk do not transfer to good decisions under uncertainty and heuristics can improve decision making under uncertainty. He shows that complex problems do not always need complex solutions. He illustrates this with a ball player. Catching a ball is a complex problem, but a player solves the problem by constantly estimating and adjusting rather than calculation (fix your gaze on the ball;

start running; adjust running speed so that angle of gaze always remain constant). The heuristic is the focus on one variable while ignoring all other information. A ball player also decides intuitively; a challenge is to work out the underlying heuristics and to teach it. It shows that less can be more, ignoring the information pays because it reduces estimation error. Another example he gave relates to an investing problem, showing that spreading your money equally over all assets proves to be more profitable than the so-called Markowitz mean variance portfolio model. The reason is that the estimation of all the parameters, not the calculation, makes the model too complex. These examples show simple heuristics could do better, safer and faster than complex models. This conclusion differs from the one from behavioral economists, like Kahneman (2011), who say that people want quick answers but pay the price with accuracy. Gigerezer's view is that only in the world of risk is that conclusion true and heuristics always second best. But in the world of uncertainty, heuristics can be better, safer and faster. Most models are typically made for risk where we know the probabilities and then fine-tuning pays. In case of uncertainty, fine-tuning does not pay, it makes the model more fragile and leads to surprises. Under uncertainty, robustness needs to be the goal, not optimization. It is therefore key to distinguish between situations of certainty (risk) and uncertainty. Uncertainty has many more dimensions than certainty. Even if you know the possible outcomes, you do not know the probabilities, so therefore you cannot optimize. It is not about people being irrational, people are rational and it would be a rational choice to use heuristics.

Finally, AI may help improve our decision making in cases where our brain unjustly neglects the low probability chances. An AI algorithm could be used as a fast thinking extension of our slow thinking brain to improve the accuracy of our fast but inaccurate brain. A simple example is an electronic calculator, a more advanced one is an adaptive cruise control that adapts smoother than many car drivers do. The potential of AI as a brain extension is enormous.

In summary, the complexity characteristics of the financial system have profound implications for regulation and risk management. The inherent sudden changes are from an overall risk management perspective unwanted. We need to strike a better balance between efficiency of actors and the vulnerability of the system. Suggestions for improvements of the resilience of the financial network are: stay at the convex side of the network, before the tipping point. Limit the size of financial institutions to avoid 'too big to fail'. Create diversity of actors. Take care for diversity of applied technology to protect against targeted attacks. Keep the rules of the system simple. Demand skin in the game to keep responsibilities and risk together. Use heuristics to deal with uncertainty provided that measures are taken to alert for inaccuracies and black swans that heuristics usually neglect, for instance AI tools.

4.6 Complexity and education

We face a number of challenges for adopting the concept of complex systems. In order to get better prepared for unexpected events we need more awareness of our misconceptions, inaccuracies, narratives and the like as described in chapter 3. We also need to be more aware of the overestimation of the use of our models with their limitations in scope and utility and their flaws in assumptions. We saw that assumptions on equilibrium and linearity are a misconception and do more harm than good. They make people believe outcomes are reliable and make them ignorant to alternative views and probability distributions. It will be challenging to release the assumption of equilibrium because most of the economic literature is based on it and outcomes may get questioned as complexity models may produce different outcomes. Causes of unexpected events should be endogenous to the model and not be blocked by the model's preconditions. Also uncertainty intervals and distributions should be part of the outcome, even if they are large. This way we get a wider variety of outcomes like distributions. Consequently we have to accept the uncertainties in the outcome, whereas in the mainstream models they often remain invisible because of the limitation of assumptions. It also means abolishing the precise looking, though inaccurate, long-term prediction that some economic forecasting models produce, as they do insufficiently take into account real-world non-linearities. Accepting that the economy is full of non-linearity, bifurcation and other chaotic behavior requires a regime change towards using complexity models that allow for extreme outcomes.

Change starts with education. Adults must learn a new approach and partly unlearn hypotheses and assumptions that are incorrect. That is quite a challenge. Reprogramming our own brain is tough as habits are deeply embedded in our brains, change in habits is hard and involves individual risk taking. Schools face the challenge of renewing the educational programs that have been used for so long. For economics, complexity is a new science overturning the old scientific paradigms, which means many teachers need to go back to school. As referred to earlier, Rickards (2014) concludes complexity has not been warmly embraced by mainstream economics, in part because it reveals that much economic research for the past half-century is irrelevant or deeply flawed. Resistance to change is to be expected. For students complexity need to be brought in a coherent way while complexity theory is still very much in development. Fichter et al. (2010) describe a method for teaching complex and evolutionary systems. Their point of departure is to overcome a number of impediments. One is the dominance of linear and equilibrium thinking and training in schools, which requires students to be familiar with mathematical principles and techniques that are presently not systematically taught. Another is the problem that evolution is now only linked to biology but needs to be taught in a wider scope. And there is the lack of both an agreed definition of complexity theory and rubrics for introducing chaos and complex systems and for modelling. Fichter et al. present answers to these challenges and propose classifications, representations and a list of rubrics to facilitate teaching and understanding the whole concept and its coherence.

The evolutionary complexity concept can also be used to further improve the educational system. Learning follows the same evolutionary path with emergence, path dependency and the stages of selection and amplification; looser structure and more randomness. Rather unstructured, it is key to offer a wide spectrum of opportunity to students, at any age. Random tinkering (antifragile) leads to heuristics, diversity, experience and skills. Taleb (2012) ironically paraphrases our educations system by 'lecturing birds how to fly': we teach students what to do what they would do anyway without help. With no attention for what failed and no attention for what hurts (iatrogenics). We could learn from games how to motivate students and let them grow through levels of difficulty which is more motivational than many of the framed assessment schemes presently in use.

Both complexity theory and exponential technologies deliberately ignore the boundaries of disciplines. To improve modelling and preparedness of all kinds of dynamics, research could benefit from a more holistic view of the matter. Like studying neurobiology and psychology to better understand our brain, brings us closer to understanding the economic behavior of agents. Knowledge of probability science to understand the impact power laws have on growth and developments allows us to better understand system dynamics, impacts of networks and exponential technologies and help us to recognize criticalities. We must abandon the absolute and embrace the realm of probability.

Adhering to the concept of complexity means making changes in the way we organize our work traditionally. Thinking in linearity and equilibrium limits our view on the real world. Many (large) organizations are designed to execute tasks, which are fixed per worker and an organizational chart reflecting the position in the hierarchy. That is Taylorism from industrial processes a century ago. In contrast, start-ups and larger organization with a clear (transformative) goal and a loose structure to achieve such goal, work more dynamically and are better adaptors. They follow an agile and lean approach, which challenges people to try, tinker and build a prototype within days or weeks, make a minimum viable product, test it with customers and improve it from there. This is applicable to basically anything, from a piece of hardware, software or professional advice. Such a lean approach stands for embracing emergent behavior. Allowing failure is part of this concept because there is no trial without error; it is part of the evolution formula. Entrepreneurs are risk takers, and risk taking is an inherent feature of man. A motto like 'failure is not an option' is perfect for communicating the high level of service a company aims to achieve, but once internalized too far into the internal culture of an organization would make people rigid and the organization more vulnerable to disruption. Risk avoidance is not an option, one should allow for experimentation which means ideas and prototypes could also fail; by the way, doing nothing is also a risk. One should take intelligent risk. Failure has in many cultures a negative connotation, or is simply not allowed, so a change in culture is needed in order to free the emergence of ideas. The track-record of existing organization to innovate and adaptation to change is limited, see Christenson (1997), Hagel and Brown (2008, 2010) and Ismail et al. (2014). This is caused by the way they are organized, the inflexible processes, the way risk is taken and the dominant efficiency thinking. Hierarchy is an efficient mechanism when a limited number of well described processes have to be executed, but are a hindrance to the process of letting ideas emerge.

4.7 Conclusions

This chapter looks at ways to get better prepared for unexpected events. The economy is assumed to behave like an evolutionary complex adaptive system. Such systems assume no central control and show emerging patterns that are different from the sum of individual behavior; such systems may show stable outcomes, but also critical states. Stable outcomes usually do not remain stable but could move to a critical stage after just a small change. Like a pile of sand that grows when you add sand following a power law, but at a certain point added sand becomes too much for the pile and a disruptive change happens totally changing the shape of the pile. The chaotic and non-linear characteristics of the economy and the financial system in particular should be recognized and as the cause of disruptive events and agent-based models could help to understand the non-linear behavior of economic and financial systems.

Complexity has been explained, as well as the evolutionary aspects of the economy and examples of models are provided. Suggestions are made for improving the financial system, along the lines of keeping the system simple and divers, as heterogeneity helps resilience of the system. We need a kind of immune system for the financial network which not only protects the system from instability but also improves its resilience to other attacks.

Adopting complexity theory in education and institutions faces resistance as it creates uncertainty over the existing theories and assumptions, and the work done based on traditional models. This is a plea for moving ahead in economic modelling, away from the assumed equilibrium thinking towards embracing evolutionary complex adaptive systems.

5 Conclusions

The spread of digitized services using networks has an increasing impact on the dynamic behavior of the economy and the financial system, reinforces them behaving as an evolutionary complex adaptive system leading to more disruptive events. People have a hard time dealing with disruptive events, even when such events can be imagined. Several explanations have been addressed, from brain functioning to mainstream economic models, which prevent us from understanding the complex behavior of the economy. Suggestions are made to get better prepared for disruptive events.

The growth of information technology will produce more non-linearities in the economy, because:

- A rapidly growing number of products and services are digitized and shift to an information-based environment. Once information-based, the pace of development grows exponentially because price/performance doubles about every two years and global networks accelerate the use of services.
- The networked society allows smart ideas to develop at accelerating speed, following a power law feature of the network and using the evolutionary blueprint of rapid idea generation, selection and amplification, potentially disrupting existing business. The result is more disruptions, shorter lifetime of companies and faster emergence of new, global dominant platforms, but also substantial price decreases because of dematerialization of products which leads to abundance.
- The result is more complexity in the economy. This trend continues as these exponential technologies potentially transform any economic sector, emphasizing the urgency to recognize the economy as an evolutionary complex adaptive system.

We often experience disruptive events as unexpected, because:

- We think less than we think we do, we are sensitive to several biases and prefer stories over facts; we have a tendency to confuse risk with uncertainty.
- We have a preference for short-term solutions and favor short-term gain over long-term risk, our perception of time is biased underestimating long-term risk and overestimating short-term risk.
- We tend to assume linearity and quickly grasp averages and normal distributions; whereas we have difficulties with thinking in non-linearities, power laws and discontinuities like phase transitions.
- Mainstream economic models incorrectly assume homogeneity of agents, completeness of information, little room for uncertainty and an equilibrium of outcome. In times of stability these models could be of help to provide direction for the short-term, but warnings for crises and other disruptions cannot be expected, and require a different approach.
- Mainstream economic models do not recognize that the economy behaves as an evolutionary complex adaptive system, which shows self-organized criticality and other higher order patterns that could be but often do not tend to equilibrium situations.

Suggestions to better understand and prepare for unwanted non-linear behavior and disruptive events:

- Accept the economy is an evolutionary complex adaptive system and not in equilibrium by default.
- Use computational agent-based models to prepare for emerging higher order patterns in the economy. Such models help us to imagine potential behavior like self-organized criticality and disruptions and allow us to experiment with impact of policy changes and their sensitivity. These models could present us a distribution of likely outcomes.

- Apply these models for short-term projections and accept that prediction and central control do not fit in complex systems because small events may cause big changes.
- It is recommended to allocate more resources to computational modelling in order to understand the systems we use and to analyze the (non-linear) impact (small) changes to the system may have. Our hands are not tied, people deal with many more complex systems around them. It will however take time, money and a change of mind to build up vast experience with such alternative way of modeling.
- Recognize that growing dependency on information services causes further complex behavior and requires to adapt systems to better cope with the features that complex systems characterize. The longer-tailed distribution feature typically makes systems more robust to random disturbances compared to normal distributed systems, but more vulnerable to targeted attacks.
- Strike a better balance between efficiency of actors and the vulnerability of the financial system. Limit the size of financial institutions to avoid 'too big to fail' and take care for diversity of actors, necessary to hold the system at the convex side, before the tipping point and keep it robust. Beyond that point the system becomes fragile.
- Incentivize skin in the game to keep responsibilities and risk together. Keep the rules of the system simple.
- Heuristics could be used to deal with uncertainty provided that measures are taken to cover the inherent inaccuracy of overlooking out-of-scope small probability, large impact events. Artificial intelligence tools could serve to keep us alert for our inaccuracies of overlooking long-tail events.
- Limit the impact of an unwanted disruption: systems under uncertainty need robustness as the main goal, not optimization. Namely we do not know when lightning strikes, but we know it will, which leaves us no other option than to limit the impact of a disruption.

- Choose resilience over efficiency also in centralized public infrastructure solutions. Even with business continuity measures like alternative sites and secured access in place, inherent vulnerabilities such as targeted attacks remain. Mitigate these risks by applying diversity in technologies, and by keeping the system simple and adaptable.
- Make the financial system antifragile by applying an immune system which improves it when being attacked. Examples would be a learning algorithm to improve cyber defense automatically when being attacked; or a large company disrupted by several new ones, adding diversity to the system and improving the industry's level of service.
- Change education to teach complex adaptive systems and related models, and teach the shortcomings of the mainstream models. Start with the math of power laws and exponentials already at primary school to show the non-linearity of life.

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Charts

Chart 1.1

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Chart 1.2

energywatchgroup.org. Data from World Energy Outlook, IEA. Reference Scenario World 2000 until 2015,projections of additional Electrical Capacity (GW) by renewables: Biomass and waste, Wind, Geothermal, Solar, Tide and wave.

Chart 2.1

Kurzweil (2005, p.67), File:PPTMooresLawai.jpg Source: http://en.wikipedia.org/w/index.php?title=File:PPTMooresLawai.jpg, License: Creative Commons. Attribution Contributors: Courtesy of Ray Kurzweil and Kurzweil Technologies, Inc. This file is licensed under the Creative Commons Attribution 1.0 Generic license. Data from singularity.com.

Chart 2.2

Kurzweil (2005, p61, p63). Data from singularity.com, from Berndt, E.R., Dulberger, E.R., Rappaport, N.J. (2000) "Price and Quality of Desktop and Mobile Personal Computers: A Quarter Century of History", MIT, A Quarter Century History of PC Prices And Quality; July 2000. ITRS, 2002 Update, On-Chip Local Clock in Table 4c: Performance and Package Chips: Frequency On-Chip Wiring Levels—Near-Term Years, p. 167. Intel transistors on microprocessors: Microprocessor Quick Reference Guide, Intel Research, http://www.intel.com/pressroom/kits/quickrefyr.htm. See also Silicon Research Areas, Intel Research, http://www.intel.com/research/silicon/mooreslaw.htm.

Chart 2.3

Kurzweil (2005, p.50), Data from singularity.com, from Electricity, telephone, radio, television, mobile phones: FCC, www.fcc.gov/Bureaus/Common_Carrier/Notices/2000/fc00057a.xls. Home computers and Internet use: Eric C.Newburger,U.S. Census Bureau,"Home Computers and Internet Use in the United States: August 2000" (September 2001), http://www.census.gov/prod/2001pubs/p23-207.pdf. See also "The Millennium Notebook," Newsweek, April 13, 1998, p. 14.

Chart 2.4

Simon Cockell, https://www.flickr.com/photos/sjcockell/8425835703. Created with Cytoascape 2.8.3 & 'random networks' plugin. Barabassi-Albert network with n=1000, m=1, s=3). Labeled for permitted free non-commercial reuse.

Chart 2.5

2.5a en.wikipedia.org, public domain. 2.5b DNB.

Chart 2.6

US Bureau of Labor Statistics, Bureau of Labor Statistics, U.S. Department of Labor, The Economics Daily, Long-term price trends for computers, TVs, and related items on the Internet at https://www.bls.gov/opub/ted/2015/long-term-price-trends-for-computers-tvs-and-related-items.htm (visited January 23, 2018).

Chart 2.7

Data from Frey and Osborne (2013), Offord University, table in appendix ranking occupations according to their probability of computerization. A selection made by DNB of occupations related to the financial sector.

Chart 2.8

Exhibit from "Building a digital-banking business", April 2016, McKinsey & Company, www.mckinsey.com. Copyright (c) 2018 McKinsey & Company. All rights reserved. Reprinted by permission.

Chart 3.1

Commons.wikimedia.org/wiki/File:Exponential.svg, public domain.

Chart 3.2

Distributions, TRENDS in Cognitive Sciences, www.cell.com.

Chart 3.3

Inspired by Taleb (2010, p.41), "One thousand and one day's of history. A Turkey before and after Thanksgiving…". Calculated with random data growth for a typical 200 days' life of a turkey.

Chart 4.1

Taleb (2012, p.443), appendix I, Nonlinearities in biology.

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