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Understanding systemic risk in financial networks by methods from statistical mechanics

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Abstract

Systemic risk is a general feature of many complex systems. The science of complex systems is a field of research that studies generalized interactions between objects that are characterized by states. Typically, the generalized interactions are mediated on networks and lead to an extremely rich phase structure, which is often more complex than that of physical systems. Systemic risk occurs in a wide variety of natural and human-made complex systems as a consequence of this phase structure. It is the risk that a large part of the system ceases to function, and collapses with potentially dramatic consequences for the system and its parts. One of the most important examples of systemic risk today is that of financial networks. The inability to see and quantify financial systemic risk poses an immense risk to society and failure to manage it has been proven to be extremely costly. It has become a focus of recent academic research, not only because of societal importance, but also for its high-precision data availability, and the situation that the financial system is human-made, and can in principle be changed and engineered to improve it. We develop a number of practical novel methods to quantify and eventually manage systemic risk. To advance the understanding of system risk, we study propagation, diffusion and synchronization mechanisms of systemic risk in not only a single layer of financial networks but on a superposition of networks, a so-called multiplex network. We present an empirical study of a financial multiplex network, which to our knowledge is based on the most detailed and comprehensive financial data currently available. The methods presented here are the first objective data-driven quantifications of systemic risk on national scales that reveal its true levels. By studying the underlying dynamical mechanisms driving the link-formation process in complex financial networks, we propose novel methods that help make financial systems safer in a self-organized critical manner. This work provides the first practical approach for management of systemic risk by re-structuring the topology of financial networks. We base our studies on both high quality data from central banks and agent-based models that were developed during this thesis.

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Outline

This thesis is a compilation of four works already published [1, 2, 3] or in review at time of writing [4]. Research for these works was conducted as part of the EC FP7 projects CRISIS, agreement no. 288501 at the Section for Science of Complex Systems at the Medical University of Vienna, at the Oxford Martin School at the University of Oxford and at the Mexican Central Bank (Banco de México). The research was carried out together with Stefan Thurner (Medical University of Vienna, International Institute for Applied Systems Analysis (IIASA), Austria and Santa Fe Institute, USA), J. Doyne Farmer (University of Oxford, UK and Santa Fe Institute, USA), José Luis Molina-Borboa (Pierre and Marie Curie University (UPMC), France), Serefín Martínez-Jaramillo (Banco de México, Mexico), Marco van der Leij (CeNDEF, University of Amsterdam, The Netherlands) and John Geanakoplos (James Tobin Professor of Economics at Yale University, USA).

With this thesis we try to progress the understanding of systemic risk in a general context, however with a strong focus on financial systemic risk, due to data availability, adaptive network topologies, and societal importance. This thesis is organized as follows. With chapter 1 we motivate the study of systemic risk. Chapter 2 discusses complex systems from a physics point of view. In chapter 3 we give an introduction to systemic risk from a complex systems perspective. In chapter 4 the methods and approaches used in this thesis to study systemic risk are discussed and data sources used for empirical study of systemic risk are described. Chapter 5 is an empirical study of a financial multiplex network with, to our knowledge, the most detailed financial data available on a financial system. In this chapter we develop a number of practical novel methods to quantify systemic risk in financial multiplex networks. In chapter 6 we study diffusion, propagation and synchronization mechanisms of systemic risk. In chapters 7 and 8 we study the underlying dynamical mechanisms driving the link-formation process in complex financial networks. In these chapters we propose novel mechanisms that make a financial system safer in a self-organized critical manner.

Contents

Chapter 1

Introduction

Physics is the natural science that involves studying all fundamental phenomena in nature. There have been several revolutions in physics that changed the kind of phenomena, which can be studied, and what can be predicted about them [5]. These changes eventually lead to the concept of complex systems that comprise of elements from statistical mechanics, quantum mechanics and chaos theory. A complex system is a system consisting of individual parts that interact with one another so that as a whole it exhibits properties not apparent from the characteristics of the individual parts. The science of complex systems is a field of research that studies generalized interactions between objects that are characterized by states. Typically, the generalized interactions are mediated on networks and lead to an extremely rich phase structure, which is often more complex than that of physical systems [6]. Methods of statistical mechanics offer an ideal framework for describing these complex systems that are common in nature and society [7]. Applying physical reasoning for studying complex systems increased the understanding of various systems, such as social systems [8, 9] biological systems [10] and economic systems [11, 12, 13, 14].

Systemic risk (SR) is a general feature of many complex systems, and applies to a wide variety of natural and human-made systems alike, ranging from ecosystems [15], to societies [16], environmental [17], and economic systems [18, 19, 20, 21]. It is the risk that a system loses its ability to function on a system-wide scale, and collapses. Typically, SR arises in systems that are composed of many components that are interconnected through strong interactions. These can be conveniently represented by networks. For example, in ecology the components could be species, the network would be the "food-web" that specifies which species eats which other species. SR is the danger that the disappearance or default of a component from the network will have severe negative consequences that can propagate and percolate through the system. This propagation might bring other nodes in distress and possibly into default. In the above example, if a specific species disappears due to an external event, this might have drastic consequences for those species whose diet depends on it. This might lead to the extinction of other species, leading to new shortages of diet for yet other species, and so on. The result can be a cascade of extinctions, massively reducing the ecosystem's diversity. The concept of cascading failure is central to the concept of SR, and makes clear from the beginning that SR is tightly related to the structure underlying network(s) of systems that are exposed to SR. Since the seminal work [22] it has become more and more clear that different network topologies can greatly influence the efficiency and stability of systems that are exposed to SR.

Maybe the most prominent example of SR today is that of financial markets - the so-called financial SR. In this context the system components are financial actors or agents like banks, insurance companies, investment funds, regulators, pension funds, etc. These agents are related with each other through networks of financial transactions and contracts, some of which depend on endogenous variables (like stock prices), and others that depend on external factors, such as weather derivatives. The particular danger of systemic financial risk has been a hot topic since the onset of the financial crisis. As before the particular danger is that a default of one financial institution might spread through the tight connections to other institutions, and might cause their default. Financial SR is the risk that the financial system as a whole or a large fraction of it can no longer perform its function as a credit provider and collapses under huge public costs. SR is a result of the network nature of financial transactions and liabilities in the financial system [23, 24, 25]. It unfolds as secondary cascades of credit defaults, triggered by credit defaults between individual counterparties. These cascades can potentially wipe out the financial system by a so-called de-leveraging cascade [26, 27, 28, 29, 30, 31, 32, 2].

Financial SR has become a focus of recent academic research, not only because of its immense importance for society, but also for its high-precision data availability, and the situation that the financial system is human-made, and can in principle be changed and engineered to improve it. Financial data is maybe the highest-quality big-data that currently exists, where the prices of millions of goods and services are known with a one-second time resolution. Several research datasets are available for financial markets that have sparked a number of recent research, such as on interbank networks [33, 24, 34, 35, 36, 37], financial flows [38], financial equities [39], overnight markets [40] and mutual cross holdings [41]. The fact that the financial system can in theory be re-designed has triggered thoughts in the direction of which network topologies are optimal in the sense of minimal SR, i.e. maximal stability at a given level of efficiency. The goal is to find ways to restructure network topologies in a way that does neither reduce the credit provision capacity of the system, which is bad for the real economy, nor the transaction volume of the financial system. Data on the topology of credit networks is available to many central banks. Several studies on historical data show typical scale-free connectivity patterns in liability networks [33, 24, 34, 35, 36, 37], including overnight markets [40], and financial flows [38].

SR is predominantly a network property of complex systems. Different network topologies (for fixed numbers of nodes and links) characterize different levels of efficiency as well as of stability of these systems. In particular, different financial network topologies will have different probabilities for systemic collapse [42]. A particular aim of this thesis is to understand the connection of efficiency and SR in networked systems. Often complex systems such as ecological, economical or financial networks are not based on a single network, but elements are connected through a multitude of different types of links. The collection of networks, linking a given set of nodes is called a *multiplex* or *multi-layer* network. In particular, for financial networks, the management of SR becomes a technical problem of managing the network topology of several financial contract networks, such as the credit-loan network, the derivative network, co-ownership network, overlapping portfolio network, and the liquidity network. The analysis of the connection of the multiplex (or multi-layer) nature of systems to their SR forms a mayor part of the thesis. For the first time, several of these network layers are available for scientific research and are made accessible to the author of this thesis.

Chapter 2

What are complex systems from a physics point of view?

2.1 What is the meaning of a prediction?

Physics is the natural science that involves the study of matter, its interactions and motion through space and time. More broadly, physicists aim at describing all fundamental phenomena in nature. Physics is an experimental science where theoretical predictions are compared with experiments. Quantitative models are used to describe phenomena and predictions are obtained through mathematical reasoning.

There have been several revolutions in physics that changed the understanding of what can be predicted [5]. In classical mechanics predictions were characterized by the principle of complete determinism. In statistical mechanics some quantities can be predicted with a small uncertainty, while for others only probabilistic prediction can be made. Quantum mechanics, in general does not predict exact values and in chaos theory predictions are only possible on a time scale smaller than the characteristic timescale of the system, because small differences in the initial conditions can result in greatly different outcomes for such systems. Thus, the meaning of a prediction has changed over time and with the systems under investigation. These changes eventually lead to the concept of complex systems that comprise of elements from statistical mechanics, quantum mechanics and chaos theory. This introduction to complex systems is based on the insights of Parisi [5].

2.1.1 Classical mechanics – exact prediction

In classical mechanics predictions are generally characterized by the principle of complete determinism. In the picture of Laplace, an intellect knowing the positions and momenta of every particle in the universe with infinite precision could exactly predict the future. This intellect is sometimes referred to as "Laplace's demon".

In classical mechanics the motion of a body is governed by Newton's laws of motion. The equations of motion for a body are given by

$$\frac{dp}{dt} = F(x), \quad \frac{dx}{dt} = \frac{p}{m} \quad , \tag{2.1}$$

where $F(x)$ is the force. With a specified force and for given initial or boundary conditions the equations of motion have a unique solution for the trajectory $x(t)$. The predicted result can be directly compared with single experiments. When repeated, the outcome of the experiment should always take the same result. Thus, in theory single experiments in classical mechanics are reproducible.

The same holds for predictions of arbitrarily complicated systems. More generally, the equations of motion $G(X)$ for a system are given by

$$\frac{dX}{dt} = G(X(t)) \quad , \tag{2.2}$$

where $X(t)$ represents the state of a system at time t, for example all positions and momenta.

In theory, solving the equations of motion for given initial conditions allows the prediction of the final state for each initial state. In reality, this becomes already an extremely difficult task for three bodies. For instance, it has been shown that there exists no general analytical solution for the famous three-body problem (sun, earth, moon).

2.1.2 Statistical mechanics – probabilistic predictions

In classical mechanics the view of the universe was that at a microscopic level mechanical laws govern all physical systems. These laws allow formulating equations of motion that precisely predict for a given initial state the corresponding future state at a later time. This view is however not useful for the description of large-scale systems with many particles. For many applications it is not necessary neither possible to know precisely all positions and momenta for each molecule in a system in order to make predictions.

In statistical mechanics this gap between the laws of classical mechanics and the practical experience of incomplete knowledge is filled. Statistical mechanics uses probability theory to predict the average behavior of a system where the microscopic state of the system is unknown.

Classical mechanics only considers a single state to predict the behavior of the system. To account for uncertainty of the microscopic details, statistical mechanics introduces the *statistical ensemble*. A statistical ensemble is a collection of independent virtual copies of the system with different microscopic details that are consistent with its observed macroscopic properties. Thus, it is a probability distribution over all possible states of the system consistent with a given macroscopic state. The concept of the statistical ensemble formalizes the notion of an experiment repeated with the same macroscopic conditions but different microscopic details that are impossible to control.

In general, this approach allows for two kinds of predictions for different quantities. Some quantities have always the same value within a small interval. These quantities can be predicted with a small uncertainty, typically of the order $N^{-\frac{1}{2}}$ for a system with N degrees of freedom. For instance for an idealized gas, with the average number of particles $\langle N \rangle$, the relative fluctuation of the particle number is given by $\langle N \rangle^{-\frac{1}{2}}$ and vanishes in the thermodynamic limit. Other quantities do not always have the same value. For these quantities probabilistic prediction can be made. For instance, the velocities of each individual molecule in a system cannot be predicted. However, it is possible to predict the probability that a molecule has a certain velocity v. For an idealized gas the distribution of velocities follows the Maxwell-Boltzmann distribution. Therefore the velocity of a molecule has to be measured several times in order to observe the distribution of velocities. If the number of measurements goes to infinity the results should approach the predicted distribution.

2.1.3 Quantum mechanics – unpredictable components

A more profound change of the understanding of what can be predicted occurred when physicists began studying the behavior of systems at atomic length scales and smaller. From the study of these systems the field of quantum mechanics gradually arose at the beginning of the twentieth century. In general, quantum mechanics does not predict exact values. Instead, it makes probabilistic predictions. It describes the probability of finding a possible outcome when measuring an observable.

The probabilistic nature of quantum mechanics has not only profound implications on what predictive means but also on the understanding of the physical world in general. This was the central topic of the famous debates between Niels Bohr and Albert Einstein. The two scientists attempted to clarify these fundamental implications with elaborate thought experiments. The consensus view of most physicists is that Bohr won the debate.

In the mathematical formalism of quantum mechanics, the state of a system at a given time is described by a state vector, sometimes referred to as a wave function. The state vector is an abstract mathematical object, which allows the calculation of probabilities for the outcomes of experiments. For example, it allows calculating the probability of finding an electron in a particular location at a particular time.

Contrary to classical mechanics, it is not possible to make simultaneous predictions of *conjugate* quantities, such as position and momentum, with arbitrary precision. For instance an electron with a known velocity may only be located somewhere within a given region of space, but it is impossible to know the exact position. Heisenberg's uncertainty principle formalizes the inability to precisely locate a particle given its conjugate momentum or vice versa. The uncertainty principle for position and linear momentum is

$$\Delta x \Delta p \geq \frac{\hbar}{2} \quad , \tag{2.3}$$

where $\Delta x = \sqrt{\langle \hat{x}^2 \rangle - \langle \hat{x} \rangle^2}$ and $\Delta p = \sqrt{\langle \hat{p}^2 \rangle - \langle \hat{p} \rangle^2}$ are the uncertainty or standard deviation of the position $\hat{x}$ and the linear momentum $\hat{p}$.

The Schrödinger equation describes the time evolution of a quantum state, similar to Newton's second law in classical mechanics. The time evolution of a quantum state is deterministic in the sense that, given a state vector at an initial time, an exact prediction for the quantum state at any later time is made. Depending on the experiment, the state vector allows calculating the probability of observing an electron in any particular location at any particular time, or the chances that its spin is oriented up or down. The actual outcome of an experiment however is in general unpredictable i.e., random. Thus, in general single experiments are not reproducible.

2.1.4 Chaos theory – prediction only until a characteristic time

In statistical mechanics the main reason for probabilistic predictions was the large number of particles present in the studied systems. In the second half of the twentieth century many systems with a small number of particles, or a small number of degrees of freedom, were discovered. For these systems it is also only possible to make probabilistic predictions.

The behavior of these systems is highly sensitive to the initial conditions. This sensitivity is sometimes referred to as the "butterfly effect". Small differences in the initial conditions can result in greatly different outcomes for such systems. In general, this does not allow for long-term prediction. This effect appears although these systems are deterministic in the sense that the initial conditions fully determine the future state. Therefore, this behavior is known as *deterministic chaos*. The field concerned with studying these systems is called *chaos theory*.

Because of the sensitivity to initial conditions, the trajectory for these systems cannot be predicted for long times. The distance of two trajectories of two systems, with very similar initial conditions, increases exponentially over time. Even a very small uncertainty of the initial condition does not allow a prediction after a characteristic time τ. For

$$X_1(0) - X_0(0) = \mathcal{O}(\epsilon) \quad , \tag{2.4}$$

the difference grows as function of the time t (as $\exp(t/\tau)$) until

$$X_1(\tau) - X_0(\tau) = \mathcal{O}(1) \quad , \tag{2.5}$$

Predictions are only possible on a time scale smaller than τ. They become impossible at later times, because it is not possible to measure initial conditions with arbitrary precision.

2.1.5 Complex Systems – unpredictable components and probabilistic predictions

More recently the existence of another class of systems was discovered. These systems may combine elements from all system discussed above. The behavior of these systems crucially depends on the detailed form of the equations of motion. Small variations in the equations of motion can lead to a large variation in the behavior of the system.

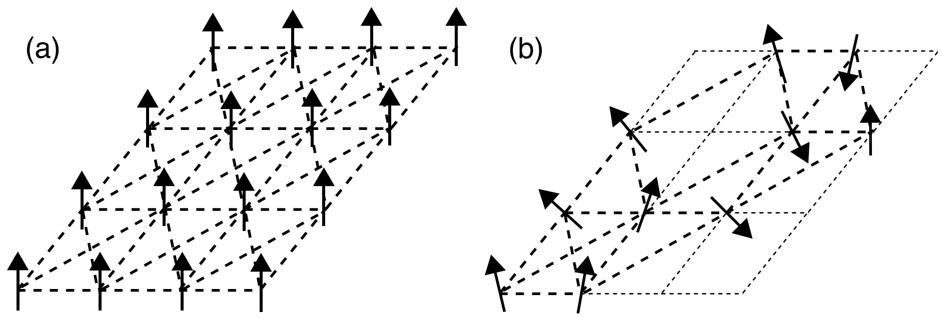


Figure 2.1: Schematic representation of a ferromagnet (a) and a spin glass (b) reproduced from [45]. Ferromagnets show an ordered spin structure while spin glasses are disordered magnets, where the magnetic moments of the atoms are not aligned in a regular pattern. Spin glasses are a prototype for a complex system in physics because of this random spin structure.

More precisely, for a system with N degrees of freedom described by the equations of motion $G_0(X)$ and $G_1(X)$ (X represents the state of a system), where

$$G_1(X) - G_0(X) = \mathcal{O}(\epsilon) \quad . \tag{2.6}$$

For a small ϵ but large ϵN the probability for the behavior of the system can be

$$P_{G_1}(X) - P_{G_0}(X) = \mathcal{O}(1) \quad . \tag{2.7}$$

The computation of the asymptotic probability as function of G is practically impossible.

Systems that exhibit this behavior are called *complex systems*. Study of these systems has opened up a new paradigm in physics [44].

2.2 Spin glasses – simple prototypes for complex systems in physics

The prototype for a complex system in physics are spin glasses. Spin glasses are the first explicit example of such a system with an extremely complex phase structure that can still be analyzed [44]. Spin glasses are disordered magnets, where the magnetic moments of the atoms are not aligned in a regular pattern. The term “glass” originates from the analogy of the molecular disorder of a conventional glass and the magnetic disorder in a spin glass.

The theory of spin glasses began with the model of Edwards and Anderson [46]. The Hamiltonian of the Edwards-Anderson model in the absence of an external field is given by

$$H = -\sum_{<x,y>} J_{xy}\sigma_x\sigma_y \quad , \tag{2.8}$$

where x and y are locations in a cubic lattice, σ_x is the spin at location x. The first sum is taken only over the nearest neighbors. J_{xy} are independent random variables chosen from a distribution such as a Gaussian with a mean zero and a variance one.

The randomness in J_{xy} of the Hamiltonian originates from the random distribution of the positions of atoms carrying spins in some spin glasses. In these spin glasses it is impossible to precisely localize the position of each atom. Therefore it is essential in the theoretical treatment to introduce random variables for J_{xy} [44].

The randomness in J_{xy} of the Hamiltonian is also a reason why it is impossible to formulate equation of motion that allow deterministic predictions. The randomness of the Hamiltonian, therefore, reflects the uncertainty of the detailed form of the equation of motion for spin glasses and a small variation in the equations of motion can lead to large variations in the behavior.

Besides simplified spin glass models like [47], which can be solved exactly [48, 49], spin glass models have been studied extensively using computer simulations, in particular *Monte Carlo simulations*. In general, the behavior of these systems may be obtained only after lengthy simulations on a computer [5].

2.3 From spin glasses to complex systems in diverse disciplines

Complex systems may combine elements from statistical mechanics, quantum mechanics and chaos theory. The behavior of these systems crucially depends on the detailed form of the equations of motion and is extremely sensitive to their exact form.

In general, complex systems can be [6]

- many particle systems (as in statistical physics),

- may have stochastic components and elements (as e.g. in quantum mechanics),
- they are often chaotic (nonlinear equations of motion),
- the behavior of the system may be extremely sensitive to the detailed form of the equations of motion,
- they can show very rich phase structure,
- and they can have many macroscopic states, which can be even simultaneously realized.

Complex systems appear in many fields, in particular in biology, economics and computer science. To expand the range of application of physical reasoning to complex systems in other fields it is possible to introduce the concept of "generalized interactions" [6]. This concept allows numerous applications of physical reasoning to problems in many diverse disciplines.

2.3.1 Complex systems as generalized interactions on networks

Central to the concept of generalized interactions is to consider interacting bodies that are not limited to matter. Generalized interactions remain based on concept of exchange. For example, in economic systems money is exchanged [13] and goods and services are traded. Another example are social systems, where messages are exchanged [50]. Just as a force in physics will change the motion of matter when unopposed, generalized interactions change the "motion" of an object in those systems. This allows formulating equations of motions for systems in biology, economics, computer science, and many other disciplines. This approach allows applying physical reasoning in countless fields.

Interactions in physical systems appear to be reducible to the fundamental interactions of nature. There are four commonly accepted fundamental interactions or forces – the gravitational, the electromagnetic, the strong, and the weak interaction. The coupling constant or gauge coupling parameter determines the strength of the respective fundamental forces. Typically the fundamental interactions operate on different scales. This means that it is often appropriate to consider only one force for a given phenomenon of interest. Other forces can be 60 (Weak, Strong), 10^4 (Weak, Electromagnetic), or up to 10^{41} (Electromagnetic, Gravitation) times stronger than the other.

Generalized interactions remain based on concept of exchange, though interacting bodies are not limited to matter. Generalized interactions differ from the fundamental forces of physical systems in the sense that they don't appear to be reducible to fundamental interactions. They typically work on similar scales. Thus, often it is necessary to consider several forces for a given phenomenon.

Generalized interactions may be specific between two objects. If there are more than two objects involved, interactions are conveniently represented by *networks*. Networks are abstract structures made up of a set of *nodes*, which are connected by a set of *links*. In this representation each object is represented by a node, and a pair of objects is connected by a link when they interact (see section 4.1).

2.4 Probabilistic predictions for complex systems

Typically, an approximate knowledge of the equations of motion does not allow predicting the behavior of a complex system. In general, the behavior of a complex system may only be predicted after time-consuming computer simulations and often even after extensive simulations the reasons for the final result remains unclear.

As an alternative Parisi [5] suggested to compute the probability of a behavior when the equations of motions are chosen randomly inside a given class. Predictions are no longer made for the properties of a complex system, but instead for the probability distribution of those properties with respect to the approximate knowledge of the equations of motion.

Obviously, this approach does not allow predicting the behavior of every particle in a system. The predictions cannot be tested on a single particle. Just like in statistical mechanics, the probability distribution of the velocities cannot be tested by measuring the velocity of a single particle. It is necessary to repeat the experiments on many different particles.

Often, the computation of the probability distribution for the behavior of a complex system can be done analytically. In particular, this applies for simple models of complex systems, like the above discussed spin glasses. For spin glasses, probabilistic predictions have been successfully verified [51].

The applications of methods that allow the computation of probability distribution of the behavior of models, which are not as simple as spin glasses, is difficult and not straight forward. Tough, the study of spin glasses has led to numerous applications to problems in biology, economics, computer science, and other fields [52].

In this thesis complex systems are studied according to this approach. The probability distribution for the behavior of the complex systems described in chapters 6 to 8 are extensively studied, for instance see sections 6.4.5, 7.4 and 8.4.

Chapter 3

What is systemic risk from a complex systems point of view?

3.1 What is systemic risk in financial systems?

SR in financial markets is the risk that a significant fraction of the financial system can no longer perform its function as a credit provider and collapses. For instance, the collapse of a bank can trigger a chain reaction that represents the same type of regime shift as a phase transition in physics [18]. In a more narrow sense SR is the notion of contagion or impact that starts from the failure of a financial institution (or a group of institutions) and propagates through the financial system, potentially to the real economy [53, 54]. In a "broad" sense SR also includes system wide shocks that affect many financial institutions or markets at the same time [53].

SR in financial markets generally emerges through two mechanisms, either the synchronization of behavior of agents (fire sales, margin calls, herding), or the interconnectedness of agents. The former can be measured by a potential capital shortfall during periods of synchronized behavior, where many agents are simultaneously distressed [55, 56, 57, 58]. The latter is a consequence of the network nature of financial claims and liabilities [23, 24, 25]. Network-based SR is potentially extremely harmful because of the possibility of cascading failure, meaning that the default of a financial agent may trigger defaults of others. Secondary defaults might cause avalanches of defaults percolating throughout the entire network and can potentially wipe out the financial system by a de-leveraging cascade [26, 27, 28, 29, 30, 31, 32, 2, 59]. The fear of cascading failure is generally believed to be the reason why institutions under distress are often bailed out at tremendous public cost [60].

SR must not be confused with default risk of nodes or links in a networked system. It is easy to illustrate this point with the example of the financial system. The risk that financial agents primarily take into account is the co-called "credit default risk", i.e. the risk that obligations (such as loans) are not payed at the agreed time, or not at all. This risk will affect the lender immediately, but does not necessarily have systemic relevance. There exists an extensive literature on the understanding, regulation, and modeling of credit default risk. The essence of present day regulation of the financial system is based on this type of risk [61, 62, 63]. Default risk exists between two counterparties once they engage in a financial transaction, and usually no network aspects are considered.

3.1.1 Definitions for systemic risk

Although literature on SR in financial systems is growing and the term SR is used for many years, there is no generally accepted definition of SR. Several authors have attempted to classify alternate definitions of SR [53, 64]. Kaufman and Scott [64] distinguishes between "big" shocks or macro shocks and shocks on the microlevel as well as on the transmission of shocks and potential spillovers from one institutions to another. Macro shocks, in this context, are shocks that produce nearly simultaneous, large, adverse effects on most or all of the financial system and the economy. Bartholomew and Whalen [65] define SR, in the sense of a macro shock, as

> *"...a systemic crisis (in the narrow and broad sense) can be defined as a systemic event that affects a considerable number of financial institutions or markets in a strong sense, thereby severely impairing the general well-functioning (of an important part) of the financial system."*.

In Mishkin [66] words, SR is related to the spread of information. It is

> *"...the likelihood of a sudden, usually unexpected, event that disrupts information in financial markets, making them unable to effectively channel funds to those parties with the most productive investment opportunities."*.

A definition for a shock on the microlevel with potential spillovers is given by Kaufman [67], where SR is the

> *"...probability that cumulative losses will accrue from an event that sets in motion a series of successive losses along a chain of institutions or markets comprising a system. ... That is, systemic risk is the risk of a chain reaction of falling interconnected dominos."*.

This is similar to the Bank for International Settlements [68], where SR is

> *"...the risk that the failure of a participant to meet its contractual obligations may in turn cause other participants to default with a chain reaction leading to broader financial difficulties."*.

For the Board of Governors of the Federal Reserve System [69] SR is also related to contagion in the payments system network.

> *"In the payments system, systemic risk may occur if an institution participating on a private large-dollar payments network were unable or unwilling to settle its net debt position. If such a settlement failure occurred, the institution creditors on the network might also be unable to settle their commitments. Serious repercussions could, as a result, spread to other participants in the private network, to other depository institutions not participating in the network, and to the nonfinancial economy generally."*.

De Bandt and Hartmann [53] differentiates between SR in a narrow and a broad sense.

> *"At the very basis of the concept (in the "narrow" sense) is the notion of contagion often a strong form of external effect working from one institution, market or system to the others. In a "broad" sense the concept also includes wide systematic shocks which by themselves adversely affect many institutions or markets at the same time. In this sense, systemic risk goes much beyond the vulnerability of single banks to runs in a fractional reserve system."*.

In the regulatory framework of Basel III, currently under discussion, the Bank for International Settlements [54] focuses also on the notion of contagion for the definition of *systemic importance*.

> *"The Committee is of the view that global systemic importance should be measured in terms of the impact that a banks failure can have on the global financial system and wider economy, rather than the risk that a failure could occur. This can be thought of*

> *as a global, system-wide, loss-given-default (LGD) concept rather than a probability of default (PD) concept."*

3.2 How does systemic risk propagate?

Financial SR can propagate through many different mechanisms and channels of contagion. In addition to default contagion, financial SR arises from asset price shocks and funding liquidity shocks [21]. Losses from asset price shocks can result in contagious failures. *Marking to market*, an accounting practice of valuing assets according to current market prices, can induce a further round of assets sales, depressing prices further and lead to "fire sales" [70]. Liquidity hoarding in interbank funding markets can cascade through a financial network with severe consequences [71, 72]. In [30] it is shown that funding of traders affects, and is affected by, market liquidity in a non-trivial way. Market liquidity and funding liquidity shocks are therefore mutually reinforcing and can lead to liquidity spirals. SR emerging from default contagion and liquidity contagion is addressed in chapters 5, 7 and 8 and SR from overlapping portfolios and the leverage cycle in chapter 6.

3.2.1 Propagation mechanisms of systemic risk in financial networks

3.2.1.0.1 Default Contagion Banks hold deposits and provide loans to other banks. Deposits and loans between banks are called *interbank* deposits and the corresponding market is called the *interbank market*. From these deposits and loans, *exposures* arise between banks. Exposure is a measure of the amount that can be lost in the event of a default of a counterparty. In the case of deposits and loans, the calculation of exposures is straightforward. Maturities and funding risk are not relevant in this context because we are only concerned with the quantification of the loss-given-default of a counterparty.

When a bank becomes insolvent, i.e. unable to pay its obligations, and is not bailed out by the government, it will go bankrupt. The creditors of the bank, including other banks, experience a loss given the default. In the short term this loss-given-default can be close to a 100% of the direct exposure between the banks [73]. If governments do not intervene and bailout banks, direct exposures can cause a chain reaction of failing banks like falling dominos and create a default cascade. This risk that a default by one institution leads to

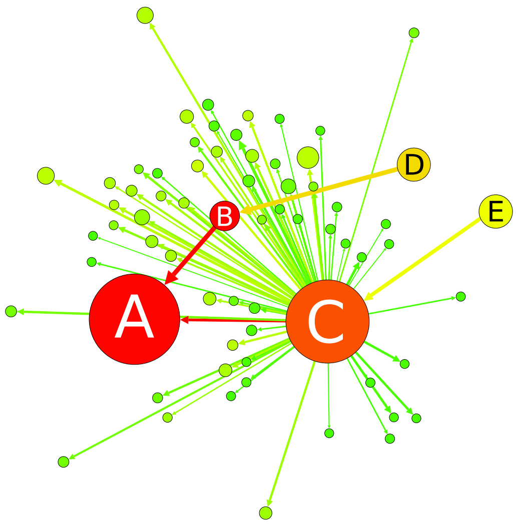


Figure 3.1: Example of a banking network. Nodes represent financial institutions or banks and directed links between the banks represent lending relations weighted by the outstanding debt. Nodes are colored according to their systemic impact R_i (see section 4.1.2): from systemically important banks (red) to systemically safe (green). Node size represents banks' total assets. Link width is the exposure size between banks, link color is taken from the counterparty.

defaults of other institutions is called contagion. Direct contagion can only occur if interbank exposures are large in comparison to the equity capital of the lender. Before the financial crisis of 2007-2008 interbank assets exceeded capital by a factor of five or more for many European banks [74].

This process can be understood from a network perspective (see also section 4.1). In a network perspective, in which nodes represent financial institutions or banks and directed links between the institutions represent lending relations weighted by the outstanding debt. Suppose, a bank A has lending relations with bank B and C. If bank A gets hit by a shock and default on its loans, B and C will experience a loss. If the capital buffers of B and C are not sufficient to absorb the loss, they will also default on their loans to their creditors D and E. This process can lead to a default cascade. Figure 3.1 illustrates this example. For a real banking network from empirical data see figs. 5.2 and 8.2.

In general, Banks interact in different markets and generate different types of exposures. Banks issue securities that are later bought by other banks. By holding these securities, banks expose themselves to other banks. Foreign exchange transactions can lead to large exposures between banks. Their exposures are associated with settlement risk. Another market activity that can lead to considerable exposures is trading in financial derivatives. From a network perspective these interactions can be represented by collection of networks. A collection of networks linking a given set of nodes is called a *multiplex* or *multi-layer* network, for details see section 4.1.3.

Although the exposures arise from different types of financial risk, the links between nodes in all the layers have the same meaning as the total loss that might arise for an institution as the consequence of the default of another. The concept and dimension of exposure is the same for all links in all layers: it is the total loss that one institution would suffer if a given counterparty defaulted (in any given layer). For an example on the constructions of a financial multiplex and appropriate netting between the different exposers see section 5.3.

Direct contagion is almost never experienced in practice. Because of the fear of cascading failure financial institutions under distress are bailed out at tremendous public cost [60].

3.2.1.0.2 Liquidity Contagion In banking, liquidity is necessary to meet obligations when they come due without incurring losses. An illiquid bank sells assets to liquid banks in exchange for cash or requests a loan from other banks. Banks hold liquid and illiquid assets. Liquid assets tend to pay less interest (cash, for example, is the most liquid asset of all but pays no interest) so banks will try to reduce liquid assets as far as possible. Maintaining a balance between short-term assets and short-term liabilities is critical and is a process called *liquidity management*. Interbank markets allow banks to exchange cash for the purposes of liquidity management. Interbank markets and *overnight markets* for short-term liquidity needs are among the most liquid markets in the financial system.

During the 2007-2008 financial crisis activity on interbank markets dropped sharply. At the same time of the "freezing" of the interbank market, interbank offered rates, the averaged interest rates at which banks offer to lend to other banks, reached record levels. Subsequently, financial institutions experienced difficulties in obtaining funding liquidity in most countries with negative influence on the entire economic system. As a consequence, central bank borrowing facilities became a critical source of funding liquidity for financial institutions [75, 76]. Several major Greek banks are seven years after the financial crisis still dependent on Emergency liquidity assistance (ELA) by the European Central Bank (ECB).

During the crisis so-called *funding liquidity shocks* took the form of *liquidity hoarding* by banks. As one bank calls in or shortens the term of its interbank loans, affected banks in turn do the same [72]. This can lead to a cascade of liquidity hoarding. From a network perspective this can be understood as follows. Suppose, bank A gets hit by a funding liquidity shock and reduces or withdraws interbank lending to bank B and C. Banks B and C then reduce or withdraw interbank lending to D and E. This process can lead to a liquidity shortage in the entire banking system and cause fears of future lack of access to liquidity [72].

3.2.2 Synchronization mechanisms of systemic risk in financial networks

Section 3.2.1 described direct exposures between financial institutions. Another form of financial contagion arises from indirect links between financial institutions. Two important mechanisms that can lead to fire sales are overlapping portfolios of financial institutions and the dynamic termed *the leverage cycle*.

3.2.2.0.1 Overlapping portfolios Financial institutions are not only connected through direct exposures, but also through indirect connections mediated by financial markets. When financial institutions invest in common assets, their portfolios overlap. This indirect connection is referred to as *overlapping portfolios*. Contagion can occur because of shocks that cause common assets to be devalued. Devaluations can cause further asset sales and devaluations leading to fire sales [70, 41, 77, 78, 79, 80].

During "the Great Moderation", a period starting in the mid-1980s until 2007, portfolios of financial institutions became increasingly similar. For example in 2007, before the financial crisis, many large banks around the world held mortgage-backed securities (MBS) and collateralized debt obligations (CDO) in their portfolios. During the U.S. subprime mortgage crisis these banks faced together write-downs and losses on the value of these investments. Together the losses on MBS and CDOs due to the subprime mortgage crisis totaled more than $500 billion [81]. In short, diversification strategies by individual institutions created a lack of diversity for the system as a whole [20].

3.2.2.0.2 Leverage cycle In finance, investing by using borrowed funds is called *leverage*. Similar to a mechanical lever that allows increasing the force, does borrowing make it possible to multiply potential gains. However, leverage increases not only potential returns but also risk. Typically, leverage is defined as the ratio of assets held to wealth. For example, an investor who buys an asset for \$100 by putting down \$20 of cash and borrowing the rest is leveraged 5 to 1. When asset prices go down, by definition, leverage goes up. Investors that want to maintain a target leverage ratio, or have a leverage constraint, are often forced to sell into falling markets. When investors sell into falling markets they cause asset prices to fall even further. This can trigger a feedback loop where selling causes falling prices, which causes leverage increases, which causes further selling. These dynamics were termed *the leverage cycle* by Fostel and Geanakoplos [27], Geanakoplos [28] (for an extensive discussion of the leverage cycle see chapter 6). In recent years a variety of studies including Adrian and Shin [29], Brunnermeier and Pedersen [30], Thurner et al. [31], Caccioli et al. [32], Poledna et al. [2], Aymanns and Farmer [59] have made it clear that deleveraging can cause systemic financial instabilities leading to market failure, as originally discussed by Minsky [26]. Thus, the leverage cycle is an import source of SR and can lead to booms and busts on a systemic level.

The leverage cycle was particularly significant in the financial crisis of 2007-2008. During "the Great Moderation" and in particular in the run-up to the financial crisis, leverage reached previously unknown levels and margins got tighter than ever before. Correspondingly, perceived volatility, as measured by the VIX (Chicago Board Options Exchange Market Volatility Index), declined consistently over the same period. During this period banks' balance sheets did not only grow together, they also stared to follow similar strategies. Similar risk management models standardized by the Basel regulatory framework, in particular Basel II, further amplified this homogeneity. Across the board, financial institutions looked alike and responded alike [20]. With the begining of the U.S. subprime mortgage crisis "the Great Moderation" came to a sudden end and asset prices started to fall. With falling asset prices the market volatility and at the same time the leverage of financial institutions started to increase. This caused further asset sales, eventually contributing to the financial crisis of 2007-2008. Thus, it is generally assumed that highly leverage and similarly risk managed institutions caused or exacerbated the financial crisis of 2007-2008 [82]. SR of the leverage cycle and the effect of current regulation policy is extensively studied in chapter 6.

3.3 Why study systemic risk?

The financial crisis of 2007-2008 and the subsequent general economic decline, sometimes referred to as "the Great Recession", showed the dramatic consequences of SR. Several years after the financial crisis of 2007-2008, millions of households worldwide still struggle to recover from the aftermath of these traumatic events. The majority of losses are indirect, such as people losing homes or jobs, and for the majority income levels have dropped substantially. For the economy as a whole, for households and for public budgets, the miseries of the market meltdown of 2007-2008 are not yet over.

These developments have spurred research on SR and financial networks. The clarification of the structure, stability and efficiency of financial networks has become a hot research topic over the past decade. It has been shown that the topology of financial networks can be associated with probabilities for systemic collapse [19, 21, 42]. In particular, network centrality measures have been identified as appropriate measures for quantifying SR according to various groups [24, 83, 84, 85, 86, 87, 3]. However, despite the tremendous importance of SR and the research efforts devoted to the topic, there are to date no reliable quantitative indices that quantify SR on a *national* and *temporal* basis. Currently there is no way of a systematic quantification of SR on the country level that would allow for a comparison of SR levels of countries or regions, and much less so for the different layers of the financial network. Indices that have sometimes been used to estimate SR in markets – such as volatility indices (like VIX), or spreads of credit default swaps (such as CDX) – are poor proxies because they are clearly incapable of taking cascading defaults into account. As a consequence these proxies greatly underestimate the true levels of SR in economies.

If SR is a network property, SR-management is largely a matter of restructuring financial networks, such that cascading failure becomes impossible [21]. In the ways SR is managed today, in academic proposals and actual implementations in legislation, this re-structuring happens indirectly. Usually systemically important institutions are taxed or are required to have larger capital cushions, which potentially lead to reduced lending which reduces SR, however at a potentially large economic cost. In chapters 7 and 8 management of SR is addressed.

Financial SR often is not only a network property, but usually is a *multiplex* (or multi-layer) network concept [3], meaning that institutions are connected by various types of links (financial contracts). The various layers of a financial multiplex network consist of the borrowing-lending contracts (obligations, i.e. counterparty exposures, and implicit relationships, such as roll-over of overnight loans), insurance (derivative) contracts, collateral obligations, market impact of overlapping asset portfolios, and networks of cross-holdings (holding of securities or stocks of other banks). Research on multiplex financial networks has appeared only recently [88, 89]. León et al. [90] are the first to study the interactions of financial institutions through different financial markets (layers) in Colombia. The estimation of SR contributions of the various layers in financial multiplex networks is completely unexplored. Quantification of SR in multi-layer networks is addressed in chapter 5.

Since data on financial networks remains hardly available outside Central Banks and is not publicly available, there have been also attempts to quantify SR without the explicit knowledge of the underlying networks [91, 55, 56, 92]. However, it remains an unsatisfactory situation that there is no objective knowledge of how much of the true SR levels are actually seen by these statistical methods, such as conditional value-at-risk (CoVaR), systemic expected shortfall (SES), systemic risk indices (SRISK) and distressed insurance premium (DIP). The problems of empirical data are addressed in chapter 5.

3.4 How to measure systemic risk?

3.4.1 Statistical measures of systemic risk

SR and financial contagion are to a large extent related to synchronized behavior and correlated portfolios of financial institutions [93, 94, 30]. In this context several econometric measures for SR have been proposed that focus (mainly) on statistics of losses, accompanied by a potential shortfall during periods of synchronized behavior, where many institutions are simultaneously distressed [55, 56, 57, 58]. In particular, four statistical measures have been proposed recently: conditional value-at-risk (CoVaR), systemic expected shortfall (SES), systemic risk indices (SRISK) and distressed insurance premium (DIP). CoVaR is defined as the value at risk (VaR) of the financial system, conditional on institutions being in distress. The contribution to SR of an institution is the difference between CoVaR, conditional on the institution being in distress, and CoVaR in its median state [55]. SES measures the propensity to be undercapitalized, given that the system as a whole is undercapitalized [56]. SES is related to leverage and the marginal expected shortfall (MES). SRISK is closely related to SES and as such a function of size of an institution, its degree of leverage, and its MES [57].

DIP measures the price of insurance against systemic financial distress in the banking system and is closely related to the expected shortfall [58].

An advantage of these approaches is that they can be computed with publicly available data, and that they are well defined in statistical terms. The disadvantage of these measures is that they are largely descriptive and that the predictive value of these measures is practically unknown. In particular, the measures based on VaR are based on historical data and can in general not be expected to work during a crisis. Therefore, it remains largely unclear how they perform as early warning signals for the build-up of SR, or how they should be used as instruments for managing SR. Most importantly, secondary and cascading-failure risk becomes very hard to estimate with these measures, since the networks of financial obligations are not explicitly considered.

3.4.2 Measuring systemic risk in financial networks

As an alternative to statistical measures of SR, it is also possible to take interactions directly into account and measure SR in financial networks. This alternative has been practically ignored by the mainstream economic literature until recently. Research on SR and financial networks has only progressed through the availability of high-precision emperical network data, such as interbank networks [33, 24, 34], financial flows [38], or overnight markets [40]. A number of recent works study the evolution of financial networks and the network formation process [76, 95, 96, 97]. Their findings indicate that a structural break only appeared after the collapse of Lehman Brothers, otherwise interbank networks remained stable during the subprime crisis. There is work that indicates that network measures could potentially serve as early warning indicators for crises [85, 86, 87].

Several *network-based SR measures* have been proposed recently. All approaches bear the notion of the *systemic importance* of a node (institution) within a financial network. It has been noticed consistently across many groups that the most relevant network property for the quantification of SR of a financial institution are network *centrality measures*, which have been applied in [24, 83, 84, 85, 86, 87, 3]. A disadvantage of centrality measures is that the value for a particular node has no clear interpretation as a measure for the level of systemic losses. An alternative to centrality measure that solves this problem is the so-called “DebtRank”, a recursive method suggested in [98] to quantify the systemic relevance of nodes in terms of losses that a node would contribute to the total loss in a crisis (see section 4.1.2). DebtRank is used in chapters 5, 7 and 8 to quantify SR and a generalized version of the DebtRank for multiplex networks is presented in chapter 5.

3.5 How is systemic risk regulated today?

In current financial regulation, SR is regulated indirectly through capital requirements and other restrictions on financial institutions. On the regulators' side, only in response to the financial crisis of 2007-2008, broader attention is now directed to financial SR. A consensus is emerging on the need for a new financial regulatory system including a potential redesign of the financial sector [99]. New financial regulation should be designed to mitigate the SR of the financial system as a whole.

In the regulatory framework of Basel III currently under discussion the importance of networks is recognized [54, 100]. In an effort for the reduction of SR, the Basle Committee on Banking Supervision (BCBS) recommends future financial regulation for *systemically important financial institutions* (SIFIs) [54]. The Basle III framework recognizes SIFIs, and in particular global and domestic systemically important banks (G-SIBs or D-SIBs), and recommends increased capital requirements for them, the so called "SIFI surcharges" [54, 100]. Here the idea is that systemically important financial institutions need to be subjected to increased capital requirements. By doing so, institutions alter their behavior and internalize contagion externalities. Instead of using quantitative models to measure systemic importance, the BCBS suggests an indicator-based approach that includes the size of banks, their interconnectedness, their substitutability, their global (cross-jurisdictional) activity and their complexity.

Basle III further introduces *counter-cyclical buffers* that allow regulators to increase capital requirements during periods of high credit growth. This should prevent synchronized risk taking of a substantial part of the financial sector. This approach to financial regulation is known as *macro prudential regulation*, and is currently put in place around the globe [99, 101, 102].

The International Monetary Fund (IMF) proposed a tax on banks (financial stability contribution, FSC) that can be seen as a contribution of the financial sector to the public costs of the financial crisis and used to build up reserves for future crises. Bank taxes have been proposed in many countries around the world, such as the "Financial Crisis Responsibility Fee" in the US. In several European countries, including Germany and Austria, bank taxes are currently in force. With the adaption of the Bank Recovery and Resolution Directive (BRRD), financial institutions of EU member states are required to contribute to the Single Resolution Fund (SRF) to finance the re-structuring of failing financial institutions. The contribution of each institution is proportional to the total liabilities adjusted by the risk profile of the institution. Similar to the Basle III indicator approach, the risk profile is assessed on the basis of four risk pillars [54]: risk exposure, stability and variety of sources of funding, importance of an institution to the stability of the financial system or economy and additional risk indicators to be determined by the resolution authority. Importance of an institution to the stability of the financial system is measured by the share of interbank loans and deposits in the EU.

In chapters 5 to 8 we discuss current regulation policies and make implementable policy recommendations that are technically feasible.

3.6 How to manage systemic risk?

Unlike for the management of credit risk, proposals for the management of SR appeared only recently. While credit risk is relatively well understood, and can be mitigated through a number of methods and techniques [103], management of SR requires an understanding of the system as a whole. While it is obvious that financial institutions as lenders have strong incentives to mitigate credit risk, it is less clear in the case of SR as it involves externalities. In general, financial institutions manage their own risks but do *not* consider their impact on the system as a whole [104]. Management of SR is, therefore, foremost in the public interest and must require financial institutions to internalize costs of SR or otherwise create an incentive to minimize risks that are borne by the public [56].

Several authors have therefore advocated various taxation schemes to manage SR [91, 55, 56, 84, 92, 105], while others are in favor of regulation due to the inherent difficulties of measuring SR [106]. Taxation schemes and the related measures for SR are typically based on the notion of *systemic importance* of financial institutions that need to be subjected to a Pigouvian tax. The idea is that institutions internalize contagion externalities if they are “taxed” based on their systemic importance. Levied taxes are typically collected by a rescue fund that can be used for bailouts. The main difference between the above proposals is the choice of the SR measure to determine the level of taxation. Several authors rely on statistical approaches [91, 55, 56, 92], whereas others use network measures [84].

These proposals share the common feature that financial institutions are subjected to taxation to alter their behavior. The reduction and mitigation of SR is therefore achieved "indirectly". Management of SR is addressed in chapter 8 with a radically different approach that involves taxation of individual contracts according to their SR-contribution to the system instead of the institutions. This approach allows to "directly" influence who is entering into a contract with whom, and to avoid systemically risky transactions in the system. It is thus possible to actively restructure the topology of financial networks in a self-organized critical manner.

Chapter 4

Methodological approaches to the study of systemic risk

SR is a general feature of many complex systems, such as the financial system. Thus, methods from other fields dealing with complex systems, including statistical mechanics, can be applied for financial systems [18, 19, 20, 21]. Complex systems, as the financial system, have the fundamental property of strong interactions between their individual parts, which typically allows representing the system as a network. Thus, a financial system can be represented by a financial network and propagation and contagion mechanisms of SR can be studied in these complex networks [24]. The consequence of a collapse of a node in a network can cause a phase transition from one equilibrium of the system to another, much less optimal equilibrium. For instance, the collapse of a bank can trigger a chain reaction that would represent the same type of regime shift as a phase transition in physics [18]. This suggests the application of agent-based modeling. Therefore, the central methodological tools of this thesis are network analysis, in particular network centrality measures, and agent-based modeling.

Financial SR often is not only a network property, but usually is a multiplex (or multi-layer) network concept [3], meaning that financial institutions are typically connected by many different links (see section 3.3). Thus, in order to analyze the multi-layer network structure of financial networks, multiplex analysis techniques (see section 4.1.3), are used in chapter 5. Often financial networks are static in size, or are only slowly growing in the number of nodes or links. This applies for instance for banking networks because the number of banks in a financial system is relatively small and stays more or less constant over time. SR can be quantified in these "quasi-static" (adiabatically growing) networks by network centrality measures, as for instance in chapter 5.

To study network formations in a financial system, i.e. to model how a network evolves over time, agent-based models (ABM) are used. ABMs further allow studying phase transitions of financial and economic systems that are associated with SR. An ABM of the real economy coupled to financial markets – the CRISIS macro-financial model – is used to study SR in chapter 8. This model was developed by a group of physicists, including the author, and economists as part of the FP7 project CRISIS and is capable of existing in different economic states or *phases* (see section 4.2.2), which is pivotal in chapter 8.

4.1 Networks to represent interactions in complex systems

Complex systems have the fundamental property of strong interactions between its individual parts and can be represented as a network. A network is an abstract representation of a set of objects where specific pairs of objects are connected. The objects are represented by *nodes* or *vertices* and the connection between the objects are called *links* or *edges*. The information of actual linking can be stored in several ways. Usually a convenient choice is to represent a network by an *adjacency matrix*, typically symbolized by upper-case letters with two subscript indices, e.g. A_{ij}. This convention is followed throughout this thesis.

Networks can be either *directed* or *undirected*. In directed networks links have a direction associated with them. They either originate or end at a particular node. In contrast, the links of an undirected network are unordered pairs of nodes. Financial networks that are studied in this thesis are always directed networks.

Networks can be described in statistical terms. One of the simplest measures is the degree distribution, $p(k)$, which is the probability of finding a node with degree k in a given network. The *degree* k_i of a particular node i in a network is the number of links connected to it. In case of a directed network the out-degree gives the number of outgoing links and the in-degree the number of incoming links, respectively. Other important measures to characterize networks are the *clustering coefficient*, c_i, the *assortativity coefficient* r, the *neighbor connectivity*, $\langle k_{nn,i} \rangle$, and the *average path length*, l. The clustering coefficient measures the probability that two neighboring nodes of a node i are also neighbors of each other, and is thus a measure for cliques in a network. The assortativity coefficient and the neighbor connectivity are measures of the degree correlation. The assortativity coefficient is the Pearson correlation coefficient of the degrees between pairs of connected nodes. The neighbor connectivity is the average degree of all the nearest neighbors of node i. The average path length is defined as the average number of steps along the shortest paths for all possible pairs of nodes in a network. It is a measure for the efficiency in terms of transportation of a network.

Networks can be classified according to their topological features. The simplest networks are completely regular lattices or completely random networks. If nodes are linked in a completely random way, the network is called a *random graph* or Erdős-Rényi (ER) network [107, 108]. Random graphs show a Poissonian degree distribution. Most networks modeling real systems such as social, ecological, and economic or financial networks show non-trivial topological features. Typically, these networks show connection patterns between their objects that are neither purely random nor purely regular. These networks are referred to as *complex networks* [109, 110].

Important complex networks that are well-known and extensively studied are so-called *scale-free* networks and *small-world* networks. A network is called scale-free if its degree distribution follows a power law. This implies that the degree distribution of this class of networks has no characteristic scale. Scale-free networks can be generated by the Barabási-Albert (BA) model using a preferential attachment mechanism [110]. A network is called a small-world network in analogy to the small-world phenomenon also known as six degrees of separation, which is the theory that everyone and everything is only separated by six or fewer steps [111]. Small-world networks are characterized by short average path lengths between the nodes and high clustering coefficients. The Watts-Strogatz model can be used to generate networks with small-world properties [112].

4.1.1 Network centrality measures

From a complex systems perspective, the most relevant network property, which can be used for the quantification of SR, are network *centrality measures*. Network centrality measures are a quantity of how *central* or how important a node is in a network [113]. They are based on the *degree* of a node, the number of links connected to it, the *closeness*, which measures the mean distance from a node to other nodes, the *betweenness*, which quantifies the fraction of paths that pass through a given node, and on the neighborhood of a node. Centrality measures that are based on the neighborhood of a node are *eigenvector centrality*, *Katz centrality* and the *PageRank*. The concept behind eigenvector centrality is that having connections to other nodes that are themselves important increases a node's importance in a network. Katz centrality corrects problems encountered with eigenvector centrality in directed networks by giving each node a small amount of centrality, regardless of the neighborhood. With regard to a bank's contagiousness, Katz centrality allows for a very good prediction of default cascades [83]. Centrality measures, in particular *Katz centrality*, have been applied to approximate SR in [114, 83, 3]. Another important variant of eigenvector centrality is the PageRank [115]. Google's search algorithm, which considers the World Wide Web (WWW) as a directed network, is based on the PageRank.

4.1.2 DebtRank – a network measure for systemic risk

The disadvantage of centrality measures is that the value for a particular node has no clear interpretation as a measure for the level of expected damage. An alternative to centrality measures that solves this problem is the so-called "DebtRank" method. It is a recursive method suggested in [98] to determine the systemic relevance of nodes in financial networks. In the context of financial markets it is a number measuring the fraction of the total economic value in the network that is potentially affected by a node or a set of nodes. DebtRank has the precise meaning of economic loss, measured e.g. in dollars, caused by the distress or default of a node. This method will be used in chapters 5, 7 and 8 to quantify SR and a generalized version of the DebtRank for multiplex networks is presented in chapter 5. We therefore provide the definition of the DebtRank in this section.

Let L_{ij} denote a financial network at a given moment (loans of bank j to bank i), and C_i is the capital of bank i. If bank i defaults and cannot repay its loans, bank j loses the loans L_{ij}. If j has not enough capital available to cover the loss, j also defaults. The impact of bank i on bank j (in case of a default of i) is therefore defined as

$$W_{ij} = \min\left[1, \frac{L_{ij}}{C_j}\right] \quad . \tag{4.1}$$

The value of the impact of bank i on its neighbors is $I_i = \sum_j W_{ij} v_j$. The impact is measured by the *economic value* v_i of bank i. For the economic value we use two different proxies. Given the total outstanding interbank exposures of bank i, $L_i = \sum_j L_{ji}$, its economic value is defined as

$$v_i = L_i / \sum_j L_j \quad . \tag{4.2}$$

Alternatively, to include also non interbank assets, the economic value can be defined as

$$v_i = (L_i + r^{loss} A_i^{tot}) / \sum_j (L_j + r^{loss} A_j^{tot}) \quad , \tag{4.3}$$

with A_i^{tot} as total assets excluding interbank assets of bank i and a constant loss rate given default $r^{loss} = 0.6$ for non interbank assets. To take into account the impact of nodes at distance two and higher, it has to be computed recursively. If the network W_{ij} contains cycles the impact can exceed one. To avoid this problem an alternative was suggested in [98], where two state variables, $h_{\mathrm{i}}(t)$ and $s_{\mathrm{i}}(t)$, are assigned to each node. h_{i} is a continuous variable between zero and one; s_{i} is a discrete state variable for 3 possible states, undistressed, distressed, and inactive, $s_{\mathrm{i}} \in \{U, D, I\}$. The initial conditions are $h_i(1) = \Psi\,, \forall i \in S_f;\ h_i(1) = 0\,, \forall i \notin S_f$, and $s_i(1) = D\,, \forall i \in S_f;\ s_i(1) = U\,, \forall i \notin S_f$ (parameter Ψ quantifies the initial level of distress: $\Psi \in [0, 1]$, with $\Psi = 1$ meaning default). The dynamics of h_i is then specified by

$$h_i(t) = \min \left[1, h_i(t-1) + \sum_{j | s_j(t-1) = D} W_{ji} h_j(t-1) \right] \quad . \tag{4.4}$$

The sum extends over these j, for which $s_j(t-1) = D$,

$$s_i(t) = \begin{cases} D & \text{if } h_i(t) > 0; s_i(t-1) \neq I, \\ I & \text{if } s_i(t-1) = D, \\ s_i(t-1) & \text{otherwise} \quad . \end{cases} \tag{4.5}$$

The DebtRank of set S_f (set of nodes in distress at time 1), is $R' = \sum_j h_j(T) v_j - \sum_j h_j(1) v_j$, and measures the distress in the system, excluding the initial distress. If S_f is a single node, the DebtRank measures its systemic impact on the network. The DebtRank of S_f containing only the single node i is

$$R'_i = \sum_j h_j(T) v_j - h_i(1) v_i \quad . \tag{4.6}$$

The DebtRank, as defined in eq. (4.6), excludes the loss generated directly by the default of the node itself and measures only the impact on the rest of the system through default contagion. For some purposes, however, it is useful to include the direct loss of a default of i as well. The total loss of default of i on the whole system, including the loss caused directly by i is

$$R_i = \sum_j h_j(T) v_j \quad . \tag{4.7}$$

4.1.3 Multi-layer networks

Often complex systems such as social, ecological, economical or financial systems are not based on a single network, but nodes are connected through many different types of links. These networks are referred to as *multiplex networks* or *multi-layer networks*. Multi-layer networks can be analyzed by network similarity measures such as node and link correlations, and link-overlap. For example, the *link-overlap* between the networks α and β counts the number of links they have in common. Mathematical, the existence of multiple connections can be expressed as a tensor $A_{ij;\alpha}$. A tensorial framework for multi-layer networks allows to generalize centrality measures, discussed above, for multiplex networks [116]. Other useful measures for multiplex networks that are used in this thesis include the *Jaccard coefficient* and the *Pearson correlation coefficient*.

4.1.3.0.1 Jaccard coefficient The Jaccard coefficient quantifies the interaction between two networks by measuring the tendency that links are present simultaneously in both networks. $J_{\alpha\beta}$ is a similarity score between two sets of elements and is defined as the size of the intersection of the sets divided by the size of their union,

$$J_{\alpha\beta} \equiv |\alpha \cap \beta| / |\alpha \cup \beta| \quad . \tag{4.8}$$

4.1.3.0.2 Correlation coefficient For two random variables X and Y with mean values $\bar{X}$ and $\bar{Y}$, and standard deviations σ_X and σ_Y, the correlation coefficient $\rho_{X,Y}$ is defined as

$$\rho_{X,Y} = \frac{E[(X - \bar{X})(Y - \bar{Y})]}{\sigma_X \sigma_Y} \in [-1, 1] \quad . \tag{4.9}$$

4.2 Agent-based models to understand complex systems

4.2.1 From spin models to agent-based models

Agent-based models (ABMs) can be used to study complex systems, in this case economic or financial systems. The central idea is that the system to be studied consists of a large number of agents – think of particles or spins – which interact with each other according to specified rules. The interactions are modeled directly in the form of (computer) algorithm and not in the form of equations. ABMs are used in statistical physics for a long time, although under different names, Cellular automata, Boolean networks and discrete models for the study of self-organized criticality [117].

ABMs are closely related to the famous *Ising model* – a model of ferromagnetism in statistical mechanics. The Ising model was originally proposed by [118] and studied by [119]. The model assumed that spins, which determine the magnetic moment of atoms or ions, could assume only two discrete states. Spins are arranged on a lattice or network and each spin interacts only with its nearest neighbors. Although the model is a simplification of reality it allows the identification of phase transitions. The two-dimensional Ising model on a square lattice is one of the simplest models that show a phase transition.

An Ising model more broadly reproduces the properties of a system where individual elements change their behavior to adapt to the behavior of the other individuals in their neighborhood. Individual parts can be atoms or molecules or more broadly proteins, animals, persons, legal entities or other phenomenon [120]. Many works in social science and economics employ concepts of the Ising model and can be mapped to different versions of it[1] [126, 127].

In a modern definition, ABMs are a class of computational models simulating the behavior and interactions of autonomous agents in order to study the behavior of the system as a whole. Table 4.1 shows a comparison between the Ising model and ABMs. The basic challenge is to understand how individual agents interact and behave locally. This allows formulating behavioral rules. The rules, in general, depend on the states and interactions with the other agents in the system and can be non deterministic. Random decisions rules represent behavior that is not correlated to other agents or events. With the

[1] See e.g. [121], [122], [123], [124] and [125].

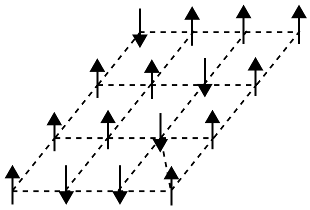
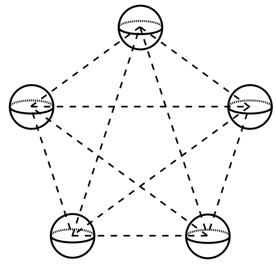
	Physics	**Complex adaptive system**
	Ising Model	ABM
		
components	particles, spins	agents
interactions	lattice	network
dynamics	Hamiltonian	algorithms
critical exponents	α, β, γ, ...	self organized criticality
critical parameters	T_c	e.g. interest rates, leverage
distributions	Boltzmann distribution	power laws
order parameter	magnetization	e.g. unemployment, output
phase transitions	simple phase diagram	complicated phase diagram

Table 4.1: Comparison Ising model and agent-based models.

behavioral rules in place a simulation is conducted to study the collective behavior of the system as a whole.

Modern ABMs typically combine elements from game theory, complex systems, multi-agent systems, evolutionary programming and cellular automata. With the growing availability and easy access to computing power, this approach gained increasing popularity since the 1990s. ABMs are currently in use in many different disciplines, including physics, material science, biology, economics, finance and social science.

ABMs in general live in high dimensional spaces. Since the behavior of ABMs typically depends on many parameters, a crucial problem is to find the most important ones. A concept from statistical physics that is particularly useful is the *phase diagram* in parameter space. A classic example of a phase diagram of a substance as a function of two parameters, i.e. temperature and pressure is shown in fig. 4.1. In ABMs typically there exist mechanisms that drive the systems toward criticality or to whole phases that are critical like in spin glasses [14].

Macroscopic or aggregated properties show only minor fluctuations in large systems and are robust against microscopic changes, but at the boundary between two phases, fluctuations can remain sizable even for large systems and

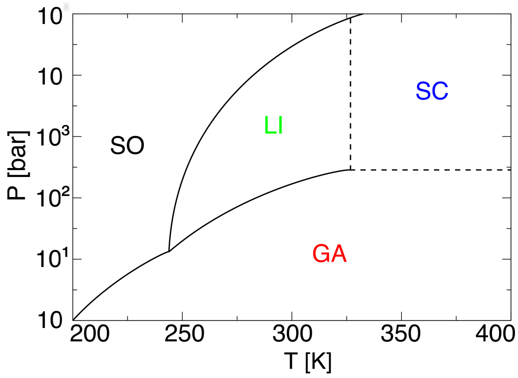


Figure 4.1: A classic example of a phase diagram with solid (SO), liquid (LI), and gas (GA) phases in the temperature-pressure plane. Above its critical point exists also a supercritical fluid phase, where distinct liquid and gas phases do not occur. Far from phase transitions, within a given phase, the behavior of the system is qualitatively similar for all parameters. Close to the boundaries of a phase, a minor change of a parameter can radically alter the macroscopic behavior of the system.

a minor change of a parameter can radically alter the macroscopic behavior of the system. With the help of ABMs it is possible to precisely monitor the events that lead to large fluctuations, like systemic failure, and how the collapse unfolds over time.

An example for an ABM of a simple economic system is [13]. Dragulescu and Yakovenko [13] study a simple closed economic system where money is conserved. In the model, each agent has some money and may exchange it with other agents. They find, by analogy with energy, that in equilibrium the distribution of money must follow a Boltzmann distribution. Statistical mechanics of this model is well understood and variables like temperature and entropy can be identified.

4.2.2 Modeling financial systems – the CRISIS macro-financial model

The CRISIS macro-financial model is an example for a detailed ABM of an economic system. The model is used in chapter 8 in order to study financial SR. The economic simulator combines a well-studied macroeconomic agent-based model [128, 129, 130] with an agent-based model of financial markets. The model was developed by a group of physicists, including the author, and economists joining forces within the *Complexity Research Initiative for Systemic Instabilities (CRISIS)*, a three-year FP7 project (2011-2014) funded by the European Commission. CRISIS is a consortium of researchers from 11 leading European academic institutions[2]. The CRISIS macro-financial model is capable of existing in different economic states or *phases* of the system and was extensively studied from a physicists perspective [14].

The aim of the CRISIS project was to build a new model of the economy and financial system that is based on how people and institutions actually behave. The simulator includes households, banks and firms. Households have various levels of wealth and are broken down into their role as consumers, workers, and the value of the house itself. Firms provide jobs and produce goods that are consumed by the households. Both households and firms will interact with banks, which provide mortgages to households and loans to firms. Finally, regulators set policies such as interest rates or collateral requirements. Moreover agents can act as investors, there is a central bank and a regulator interacting on various markets including an interbank market, a stock market and a commercial loan market. To capture the interbank market and firm-bank credit networks, the model allows the possibility for strategic behavior of agents. The simulator allows studying the formation of bubbles and crises, as well as regimes of stability, from the bottom-up. The simulator is written in Java within the MASON framework, a multi agent simulation library.

In the model, there are three types of agents: households, banks, and firms, as depicted in fig. 4.2. The agents interact on four different markets:

(i) Firms and banks interact on the credit market.

(ii) Banks interact with banks on the interbank market.

(iii) Households and firms interact on the job market.

(iv) Households and firms interact on the consumption goods market.

Banks hold all firms' and households' cash as deposits. Households are randomly assigned as owners of firms and banks (share-holders). Agents repeat the following sequence of decisions at each time step:

[2]The consortium included: Università Cattolica del Sacro Cuore (UCSC), University of Oxford, Universiteit van Amsterdam (UvA), Centre de Recerca en Economia Internacional (CREI), Medizinische Universität Wien (MUV), The City University (CITY), AITIA International, Inc. (AITIA), Università degli Studi di Palermo (UNIPA), Commisariat à l'Energie Atomique et aux Energies Alternatives (CEA), Università Politecnica delle Marche (UPM) and Scuola Normale Superiore di Pisa (SNS).

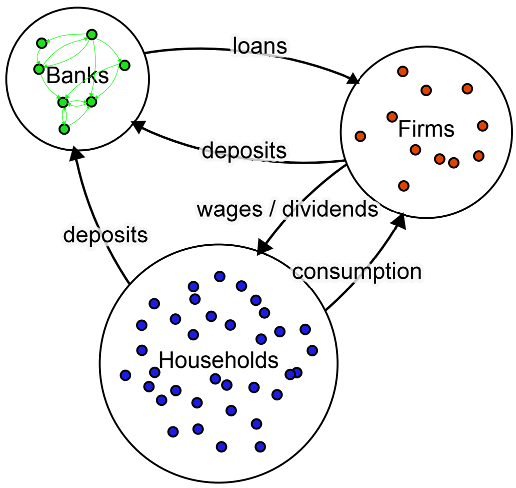


Figure 4.2: Schematic overview of the model structure showing the three agent types (banks, firms, and households), and their interactions. Firms pay dividends to their owners, and wages (financed through income and loans) to their workers. Households consume goods produced by the firms. Households and firms deposit money in banks, banks grant loans to the firms.

1. firms define labour and capital demand,
2. banks raise liquidity for loans,
3. firms allocate capital for production (labour),
4. households receive wages, decide on consumption and saving,
5. firms and banks pay dividends, firms with negative liquidity go bankrupt,
6. banks and firms repay loans,
7. banks raise additional liquidity to manage unanticipated cash needs.

Households owning firms or banks receive dividends as income. All other households earn salaries. Banks and firms pay 20% of their profits as dividends.

4.2.2.1 The agents and their properties/states

We give a short description of the agents; for more details on the agents and their interactions, see Delli Gatti et al. [130] and Gualdi et al. [14].

4.2.2.1.1 Households There are H households of which there exist two types: firm owners, and workers. Each of them has a personal account $A_{j,b}(t)$ at one of the B banks. j indexes the worker, b the bank. Household accounts are randomly assigned to banks. Workers apply for jobs at the F different firms. If hired, they receive a fixed income w per time step, and supply a fixed labour productivity α. Firm owners receive their income through dividends from their firm's profits. At each time step every household spends a fixed percentage c of its current account on the goods market. They compare prices of goods from z randomly chosen firms and buy the cheapest.

4.2.2.1.2 Firms There are F firms producing perfectly substitutable goods. At every time step firms compute an expected demand $d_i(t)$, and an estimated price $p_i(t)$ (subscript labels the firm), based on a rule that takes into account both excess demand/supply and the deviation of the price $p_i(t-1)$ from the average price in the previous time step [130]. Each firm computes the number of required workers to supply the expected demand. If the wages for the respective workforce exceed the firm's current liquidity, it applies for a loan. Firms approach n randomly chosen banks and choose the loan with the most favorable rate. If this rate exceeds a threshold rate $r^{\max}$, the firm only asks for ϕ percent of whatever loan was originally requested. Based on the outcome of this loan request, firms reevaluate the required workforce, and hire or fire the necessary number of workers. Firms sell the goods on the consumption goods market. Firms go bankrupt if they have negative liquidity after the goods market has closed. Each of the bankrupted firm's debtors (banks) incurs a capital loss in proportion to their investment in the company. Firm owners of bankrupted firms are personally liable, and their personal account is divided by the debtors *pro rata*. They immediately (next time step) start a new company. Their initial estimates for $d_i(t)$ and $p_i(t)$ equals the respective current averages in the population.

4.2.2.1.3 Banks There are B banks that offer firm loans at rates that take into account the individual specificity of banks (modeled by a uniformly distributed random variable), and the firms' creditworthiness. Firms pay a credit risk premium according to their creditworthiness, which is modeled by a monotonically increasing function of their financial fragility [130]. Interest rates offered by banks to firms is determined as a mark-up over a benchmark interest rate $\bar{r}$. Banks try to provide requested loans and grant them if they have enough liquid resources. If they do not have enough cash, they approach other banks in the interbank market to obtain the necessary amount. If a bank does not have enough cash and cannot raise the full amount for the requested firm loan on the interbank market it does not pay out the loan. Interbank and firm loans have the same duration. Additional refinancing costs of banks remain with the firms. Each time step firms and banks repay τ percent of their outstanding debt (principal plus interest). If banks have excess liquidity they offer it on the interbank market for a nominal interest rate. The interbank market is modeled after an electronic marketplace where, in principle, all participants can enter into business relationships. In the model, banks choose the interbank offer with the most favorable rate. This does not mean that the emerging interbank network is fully connected. Emerging interbank networks are shown in fig. 8.1 and (weighted) degree distributions can be found in fig. 8.6. Interbank rates $r_{ij}(t)$ offered by bank i to bank j take into account the specificity of bank i, and the creditworthiness of bank j. If a firm goes bankrupt the respective creditor bank writes off the respective outstanding loans as defaulted credits. If the bank does not have enough equity capital to cover these losses, it defaults. Following a bank default an iterative default-event unfolds for all interbank creditors. This may trigger a cascade of bank defaults. For simplicity's sake, we assume no recovery for interbank loans. This assumption is reasonable in practice for short term liquidity [73]. A cascade of bankruptcies happens within one time step. After the last bankruptcy is taken care of the simulation is stopped.

4.2.2.2 Phase diagram of the CRISIS macro-financial model

The CRISIS macro-financial model is capable of existing in different economic states or *phases* of the system. A main property of the model is the existence of a first order phase transition between the different economic states [14]. The model essentially exists in two stationary states with a first order discontinuous transition line dividing the two states. If parameters are chosen as such that the economic system is close to this transition line, a small perturbation can be amplified and lead to a phase transition from an economic state characterized by high output and low unemployment (boom) to a state with low output and high unemployment (bust). The proximity of the parameters to the transition line leads to oscillations of booms and busts.

This phase transition is closely related to the parameter setting of the interest rates in the model, in particular the parameter of the benchmark refinancing rate $\bar{r}$. Interest rates of firms are approximately given by $\bar{r}$ (refinancing costs of banks) plus a credit risk premium according to their creditworthiness. A discontinuity appears in the model when average interest rates of firms exceed

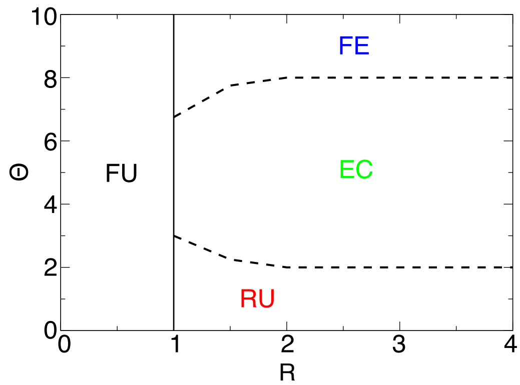


Figure 4.3: Phase diagram of the CRISIS macro-financial model reproduced from [14]. The ratio R is the asymmetry between the rate of hiring and the rate of firing of the firms. The leverage ratio Θ controls the ratio between total assets and total liabilities. In region 1 ("FU"), for $R < 1$, the model is in a phase with full unemployment. Region 2 ("RU"), with very low Θ, shows persistent "residual unemployment" in a large region where $R > R_c$. In region 4 ("FE"), for very large Θ, a phase with full employment exists. Region 3 ("EC"), for intermediate values of Θ, shows an interesting phase were "endogenous crises" appear. Here the unemployment rate is typically very close to zero but endogenous crises can occur and the unemployment rate can spike to reach large values.

a threshold rate $r^{\max}$, where a firm only asks for a fraction of the originally desired loan volume. This causes a credit contraction and leads to a first order phase transition. The reason for the phase transition is that the credit contraction introduces an asymmetry in the hiring/firing process of firms. When firms are highly indebted, they hire workers at a slower rate which in turn shifts the steady-state of the economy [14]. This generic phase transition is a noteworthy result, since many properties are qualitatively similar within the phases. This offers a solution for the problem of high dimensionality and huge parameter spaces, which many large ABMs suffer from. Often it is sufficient to understand the generic properties of the system within a phase in order to describe its behavior. In chapter 8 we study the system in a economic state characterized by high output, low unemployment and large credit demand.

In order to visualize the different phases of the CRISIS macro-financial model Gualdi et al. [14] simplified the model. In the simplified model the household sector is represented by aggregate variables and the banking sector is removed. Firms and the household sector only have deposit accounts. Only firms are kept as individual agents and loans are models by allowing deposits with a negative balance. For a complete description of the simplified model and parameter values, see [14].

However, most parameters are not important for the aggregate qualitative behavior of the model. Only the ratio R, which represents the asymmetry between the rate of hiring and the rate of firing of the firms and the leverage ratio Θ, which controls the ratio between total assets and total liabilities, are important for the state of the system. Gualdi et al. [14] finds that for a given set of parameters, there is a critical value R_c separating the full unemployment phase for $R < R_c$ from the phase where some of the labour force is employed for $R > R_c$.

Figure 4.3 shows the phase diagram of the simplified CRISIS macro-financial model in the $R - \Theta$ plane. For $R < 1$ (region 1, "FU") we encounter a phase with full unemployment. For very low Θ (region 2, "RU"), we have persistent "residual unemployment" in a large region where $R > R_c$. For R close to $R = R_c$ the unemployment rate is as high as 0.5. With increasing values of R and Θ the unemployment rate decreases continuously. For very large Θ (region 4, "FE"), a phase with full employment is encountered. For R around $R \approx R_c$ low unemployment appears in a narrow region. With increasing Θ, the width of this region of small unemployment disappears. For intermediate values of Θ (region 3, "EC") an interesting phase with "endogenous crises" appears. Here the unemployment rate is typically very close to zero but endogenous crises can occur. As a crisis occurs the unemployment rate can spike to reach large values.

4.3 Data sources for agent properties/states and interactions

The works presented in chapters 5, 7 and 8 are directly related to empirical data of financial networks.

4.3.1 Austrian interbank network data

One of the first data sources for interactions in interbank networks is the database of the Austrian Central Bank (OeNB). This data source contains anonymized Austrian interbank exposure data from the entire Austrian banking system. Included is data on about 800 banks over 12 consecutive quarters from 2006-2008. In addition to the complete interbank exposure networks, the data source contains balance sheet data including total assets, total liabilities, assets due from banks, liabilities due to banks, and liquid assets (without interbank assets/liabilities) for all banks. The data is fully anonymized, and linearly transformed. The data source has been studied by researchers from the Section for Science of Complex Systems and the Austrian Central Bank (OeNB), for instance see [34, 24, 38].

4.3.2 Mexican multi-layer network data

A unique data source that can be used to study multiplex aspects and is a database on exposures at the Banco de México. The database is built and operated with the specific purpose of studying contagion and SR. The data source contains daily information on the exposures between 40 Mexican banks from 2007-present. The transactions included as part of the bilateral exposures on the database are: daily cross-holding of securities between banks, securities lending and securities used as collateral, as well as daily exposure arising from the valuation of repo transactions and from securities trading. Daily exposures arise also from the valuation of derivatives transactions, including swaps, forwards and options. Further, the database contains daily interbank deposits and loans in local and foreign currency, credit lines extended for settlement purposes and exposures arising from securities lending related activities, as well as all daily FX transactions. Various balance sheet data on the 43 Mexican banks is also included. The data set has been used in [131] and in chapter 5.

The database is maintained by the statistics unit at the financial stability general directorate at the Banco de México. The statistics unit under the financial stability general directorate at Banco de Mexico gathers information and cross-validates it by using daily, weekly, and monthly regulatory reports, which are used for regulatory and supervisory purposes. An illustrative and important example is the case of the daily regulatory reports known as "operaciones de captación e interbancarias en moneda nacional y udis" (OCIMN), and "operaciones de captación e interbancarias en moneda extranjera" (OCIME). These reports contain every single funding transaction on a daily basis in local and foreign currency, which are used to compute the daily funding costs for each bank. From these two regulatory reports it is possible to compute the exact daily unsecured exposures between banks, as well as more broadly, the exposures between financial institutions like investment banks, brokerage houses, mutual funds, and pension funds. In Solorzano-Margain et al. [132], a stress testing study was carried out using an (extended set) of these exposures. Given the confidential nature of these transactions, data are kept under strict access control and can only be used for regulatory, supervisory and financial stability purposes.

4.3.3 Electronic market data

An open data source is the anonymized database from the Italian electronic broker market for interbank deposits (e-MID). It contains records of millions of interbank transactions from 1999 to 2009 and is used by around 250 market players from 16 EU countries and accounts for $\sim 17\%$ of total turnover in unsecured money markets in the Euro area. Data contains the exact time (at the second level) of the transactions, the maturity of contracts, a code labelling the quoting bank, i.e. the bank that proposes a transaction, a code labelling the aggressor bank, i.e. the bank that accepts a proposed transaction, the lending rates, the lending bank will receive (expressed per year), the volume of the transaction is expressed in millions of Euros, a code representing their country volume, and (for Italian banks only), a label that encodes their size, as measured in terms of total assets. This data set has been studied extensively by many researchers, for a recent work, see e.g. [76, 95, 96].

Chapter 5

Measuring systemic risk in financial multi-layer networks

5.1 The problems of empirical data

Empirical data on financial networks is in general not publicly available and is typically collected and owned by central banks or other government agencies. Because of the confidential nature of financial network data these agencies are reluctant to allow researches access the data. As a result, research on financial networks has mainly focused on credit networks between financial institutions [33, 24, 34, 35, 40, 36, 37, 96, 95]. However, institutions are connected by contracts of various types. Different contract types can be seen as various network layers. A collection of various networks linking the same set of nodes is called a multi-layer or multiplex network. The various layers of the financial multi-layer network consist of the credit (borrowing-lending relationships, consisting of counterparty exposures and implicit relationships, such as roll-over of overnight loans), insurance (derivative) contracts, collateral obligations, market impact of overlapping asset portfolios and the network of cross-holdings (holding of securities or stocks of other banks).

In recent years, several contributions to the statistical understanding of multi-layer networks and their dynamics have appeared in a broad and general context [133, 134, 135]. Network similarity measures, node- and link correlations, and link-overlap measures have especially turned out to be useful tools for identifying and quantifying interactions between layers [134, 135, 133]. The various layers of a financial multi-layer network comprise credit (borrowing-lending relationships consisting of counterparty exposures and implicit relationships, such as rollover of overnight loans), insurance (derivative) contracts, collateral obligations, and the market impact of overlapping asset portfolios and network of cross-holdings (holding of securities or stocks of other banks). Research on financial networks has mainly focused on a single layer: mostly, on direct lending networks between financial institutions [33, 24, 34, 35, 40, 36, 37, 96, 95], but also on the network of derivative exposures [84, 136], and on the network of common asset exposures [137]. Research on financial *multi-layer* networks has only appeared recently. León et al. [90] study the interactions of financial institutions on different financial markets in Colombia. Bargigli et al. [89] study the interaction in the Italian interbank market between financial network layers of short- and long-term bilateral lending, both secured and unsecured. Bargigli et al. [89] and León et al. [90] are however not directly concerned with measuring SR.

Bluhm et al. [138] consider an agent-based model of a multi-layer interbank network, incorporating different contagion channels – i.e., from common asset exposure, direct lending exposures, and fire sales. They are not concerned with the interaction between the individual layers. On the other hand, Montagna and Kok [88] do consider the contribution of individual contagion layers to SR. Their agent-based model consists of three layers: long-term direct lending exposures, short-term direct lending exposures, and common asset exposures. Calibrating the model on end-of-2011 balance sheet data from 50 European banks, they obtain a similar result to us, namely, that SR measured on the combined multi-layer network can be much larger than the aggregate SR from the individual network layers. However, Montagna and Kok [88] do not have actual bilateral network data at their disposal; instead, they consider the multi-layer network structure as a free parameter in their calibration exercises, and SR depends on the network structure considered. By using daily data on the exact bilateral exposures between banks in the Mexican financial network, our work, however, does not allow for this freedom. The use of high frequency longitudinal data allows a detailed analysis of the fluctuations of different SR contributions over time. Furthermore, Montagna and Kok [88] do not consider exposures from derivatives, cross-holdings of securities, and FX transactions, which in the Mexican data set turn out to be the dominant exposures and thus more relevant than short-term or long-term unsecured deposits & loans. Moreover, whereas Montagna and Kok [88] consider as a measure of systemic risk the number of failing banks in a default cascade, we consider a measure of systemic risk based on DebtRank which allows for a simple interpretation of SR in terms of expected losses and a simple comparison to market-based systemic risk measures. Thus, the availability of more granular and extensive data allows us to take the analysis of Montagna and Kok [88] a considerable step further.

In this context several risk measures for SR have been proposed that focus (mainly) on statistics of losses, accompanied by a potential shortfall during periods of synchronized behavior, where many institutions are simultaneously distressed [55, 56, 57, 58]. In particular, four statistical measures have recently been proposed: conditional value-at-risk (CoVaR), systemic expected shortfall (SES), systemic risk indices (SRISK), and distressed insurance premium (DIP). CoVaR is defined as the value at risk (VaR) of the financial system, conditional on institutions being in distress. The contribution to SR of an institution is the difference between CoVaR, conditional on the institution being in distress, and CoVaR in its median state [55]. SES measures the propensity to be undercapitalized, given that the system as a whole is undercapitalized [56]. SES is related to leverage and the marginal expected shortfall (MES). SRISK is closely related to SES and as such, a function of the size of an institution, its degree of leverage, and its MES [57]. DIP measures the price of insurance against systemic financial distress in the banking system and is closely related to the expected shortfall [58]. None of these measures take cascading defaults into account.

In this chapter we develop a number of potentially practical methods to quantify SR in financial multi-layer networks. First, we extend the notion of systemic importance in financial networks to multi-layer networks. This makes it possible to assess SR contributions from various layers of financial networks. Second, we develop a risk measure to quantify the expected loss due to SR, that takes cascading into account by explicit use of financial network topologies on a daily scale. This risk measure extends the notion of systemic importance to a national level and allows us to compare the SR levels of economies over time and to identify trends and historical events. In this sense the measure can be used as an indicator or an SR index. In particular it makes it possible to compare SR levels and their related potential costs before and after the recent crisis. Third, building on the work of Poledna and Thurner [4], we use the risk measure to quantify the marginal contribution of individual exposures in financial networks to the overall SR. This allows us to extend the notion of systemic importance from financial institutions to individual exposures. In particular it allows us to quantify the expected loss due to SR associated with every individual exposure of financial institutions.

This work is based on a unique data set containing various types of daily exposures between the major Mexican financial intermediaries (banks) over the period 2004-2013 (for this work we use data from 2007-2013). Data were collected and are owned by the Banco de México and various aspects of the data have been extensively studied [139, 140, 131]. Here we focus on banks that interact simultaneously in four different markets, generating four different types of exposures: (unsecured) interbank credit, securities, foreign exchange, and derivative markets. Hence, institutions are connected by four different types of contract. Different contract types can be seen as distinct network layers. A collection of various networks linking the same set of nodes is called a multi-layer or *multiplex network*. The interplay of the various exposure networks can be represented as layers in a financial multi-layer network. The data further contains the capitalization of banks for every month. With this data we quantify the SR contributions of the individual layers and estimate the mutual influence of one layer of exposures on the others.

5.2 Quantification of systemic risk in multi-layer networks

5.2.1 The financial multi-layer network – different exposure types

Banks interact in different markets and generate different types of exposure. Banks issue securities that are later bought by other banks. By holding these securities, banks expose themselves to other banks. Foreign exchange transactions can lead to large exposures between banks. Their exposures are associated with settlement risk. Another market activity that can lead to considerable exposures is trading in financial derivatives.

We analyze four different types ($\alpha = 1, 2, 3, 4$) of financial exposure: "derivatives," "securities," "foreign ex-change," and "deposits & loans." In section 5.3 we explain in detail how the exposure types are obtained from the Mexican data set. We use the following notation for different exposure types: the size of every exposure of type α of institution i to institution j at time t is given by the matrix element $L_{ij}^{\alpha}(t)$. $\alpha = 1, 2, 3, 4$ labels the layers "derivatives," "securities," "foreign exchange," and "deposits & loans," respectively. We use the convention to write liabilities in the rows (second index) of matrix L, so that the entries $L_{ij}^{\alpha}(t)$ at a given day t are the liabilities bank i has toward bank j. If the matrix is read column-wise (transpose of L) we obtain the assets or exposures of banks. Although the layers considered in this work arise from different types of financial risk, the links between nodes in all the layers have the same meaning as the total loss that might arise for an institution as the consequence of the default of another. The concept and dimension (dollars) of exposure is the same for all links in all layers: it is the total loss that one institution would suffer if a given counterparty defaulted (in any given layer), for details see section 5.3.

5.2.2 DebtRank – quantification of systemic risk at the institutional level

DebtRank was originally suggested as a recursive method to determine the systemic relevance of nodes within financial networks [98]. It is a quantity that measures the fraction of the total economic value V in the network that is potentially affected by the distress of an individual node i, or by a set of nodes S. For details see section 4.1.2. The DebtRank of a set of nodes S that is initially in distress is denoted by R_S. In those cases where only one node i is initially under distress (the set S contains only one node i) we denote the Debt Rank of that node by R_i.

DebtRank values can be computed for each layer of a multi-layer network, L_{ij}^{α} separately. For DebtRanks of layer α, R_i^{α}, L_{ij} in eq. (4.1) is simply replaced by L_{ij}^{α}. The economic value at each layer that is necessary for the computation of R_i^{α} is given by $v_i^{\alpha} = L_i^{\alpha} / \sum_j L_j^{\alpha}$, where $L_i^{\alpha} = \sum_j L_{ji}^{\alpha}$. For a multi-layer network, DebtRank can be calculated from the combined liability network $L_{ij}^{\mathrm{comb}} = \sum_{\alpha} L_{ij}^{\alpha}$. We refer to the DebtRank of the combined liability network as R_i^{comb} and the total economic value $V^{\mathrm{comb}} = \sum_i L_i^{\mathrm{comb}}$ is given by total interbank assets in all layers combined, see eq. (4.2).

To allow a comparison of R_i^{α} between different layers, R_i^{α} must be shown as a percentage of the total economic value V^{comb} of interbank assets in all layers combined (eq. (4.2)). The normalized DebtRank for layer α is therefore defined as

$$\hat{R}_i^{\alpha} = \frac{V^{\alpha}}{V^{\mathrm{comb}}} R_i^{\alpha} \quad , \tag{5.1}$$

where $V^{\alpha} = \sum_i L_i^{\alpha}$ is the total economic value of the interbank assets in the layer α.

5.2.3 Quantification of systemic risk at the country level

We define the *SR-profile* of a country at time t as the rank-ordered normalized DebtRank values $\hat{R}_i^{\alpha}$ for all financial institutions in a country. The SR-profile shows the distribution of systemic impact across institutions throughout a country. The institution with the highest SR level is to the very left. We denote the number of institutions in a country by b. It is natural to define the average DebtRank as a quantity that captures the SR of the entire economy (with b institutions) at a given time,

$$\bar{R}^{\alpha}(t) = \frac{1}{b}\sum_{i=1}^{b} \hat{R}_i^{\alpha}(t) \quad . \tag{5.2}$$

For the combined network, $\hat{R}_i^{\alpha}$ is replaced by R_i^{comb}, and we write $\bar{R}^{\text{comb}}(t)$ for the combined average DebtRank. Note that $\bar{R}^{\alpha}(t)$ depends on the network topology of the various layers (or the combined network) only and is independent of default probabilities, recovery rates, or other variables.

The precise meaning of the DebtRank as the fraction of the total economic value in a network allows us to define the *expected systemic loss* for the entire economy, which is the size of the loss, multiplied by the probability of that loss occurring [4]. To compute the expected systemic loss, we first consider the simple case where only one institution i can default and all other $b-1$ institutions survive. In this case the expected loss is given by $\text{EL}_i^{\text{syst}}(\text{one default}) = V \cdot p_i \cdot (1-p_1) \cdot \ldots \cdot (1-p_{i-1}) \cdot (1-p_{i+1}) \cdot \ldots \cdot (1-p_b) \cdot R_i$, where p_i is the probability of default of institution i, and $(1-p_j)$ the survival probability of j. The general case occurs when we also consider possible joint defaults, meaning that a set of institutions S go into distress. Taking into account *all* possible combinations of defaulting and surviving institutions, we arrive at a combinatorial expression of the expected loss for an economy of b institutions

$$\text{EL}^{\text{syst}} = V \sum_{S\in\mathcal{P}(B)} \prod_{i\in S} p_i \prod_{j\in B\setminus S} (1-p_j)\, R_S \quad , \tag{5.3}$$

where $\mathcal{P}(B)$ is the power set of the set of financial institutions B, and R_S is the DebtRank of the set S of nodes initially in distress. $R_{\emptyset}$, the DebtRank of the empty set is defined as zero. The reason is that, by definition of DebtRank, $R_S \leq 1$, the value obtained in eq. (5.3) cannot exceed the total economic value. Note that the same arguments apply equally for individual network levels or the combined multi-layer network, where EL^{syst} can be calculated with R_i^{α} or R_i^{comb}, in combination with the corresponding economic values eq. (4.2).

It is immediately clear that eq. (5.3) is computationally feasible only for situations with relative small numbers of financial institutions. Computing the power set and calculating DebtRanks for all possible combinations of large financial networks is unfeasible. If the default probabilities are low ($p_i \ll 1$) or the interconnectedness is low ($R_i \approx v_i$), R_S can be approximated by

$$R_S \approx \sum_{i \in S} R_i \quad . \tag{5.4}$$

In an unconnected or unleveraged financial system ($R_i = v_i$), R_S is exactly equal to $\sum_{i \in S} R_i$. If $p_i \ll 1$, the first terms of eq. (5.3) (with only one node initially in distress) contribute more to the final result. Thus the approximation eq. (5.4) has only a minor impact on the final result. Typically, $p_i \ll 1$ or $R_i \approx v_i$ holds in real word financial networks. With the approximation eq. (5.4), eq. (5.7) can be derived from eq. (5.3) by

$$\begin{aligned}
\mathrm{EL}^{\mathrm{syst}} &\approx V \sum_{S \in \mathcal{P}(B)} \prod_{i \in S} p_i \prod_{j \in B \setminus S} (1 - p_j) \left(\sum_{i \in S} R_i \right) && (5.5) \\
&= V \sum_{i=1}^{b} \underbrace{\left(\sum_{J \in \mathcal{P}(B \setminus \{i\})} \prod_{j \in J} p_j \prod_{k \in B \setminus (J \cup \{i\})} (1 - p_k) \right)}_{=1} p_i \, R_i && (5.6) \\
&= V \sum_{i=1}^{b} p_i \, R_i \quad . && (5.7)
\end{aligned}$$

The term in brackets in eq. (5.6) sums to 1 (proof by induction). This approximation is practical for large financial networks and is certainly valid if the default probabilities are low ($p_i \ll 1$), or the interconnectedness is low ($R_i \approx v_i$). To show that the approximation is extremely precise as far as realistic scenarios are concerned, we compare the exact result of eq. (5.3) with the approximation eq. (5.7) for an economy of 15 banks. Note that in principle eq. (5.7) can become larger than V. However, in fig. 5.1 we show that the approximation is a maximum of 3.5% off the exact value of eq. (5.3), which is never larger than V. For larger sets of banks, such as the Mexican data set, we would run into computational difficulties in computing the 17 billion odd combinations. For the remainder we will, therefore, use eq. (5.7).

We test the quality of the approximation for $\mathrm{EL}^{\mathrm{syst}}$ with respect to the exact result given in eq. (5.3). In fig. 5.1 we show the exact result for $\mathrm{EL}^{\mathrm{syst}}$ considering only the 15 largest Mexican banks (blue line), which can still be computed in reasonable time. The approximation of eq. (5.7) is shown in red (dashed). The approximation is generally higher than the exact result (on average less than 0.65%). The maximum deviation is 3.5%.

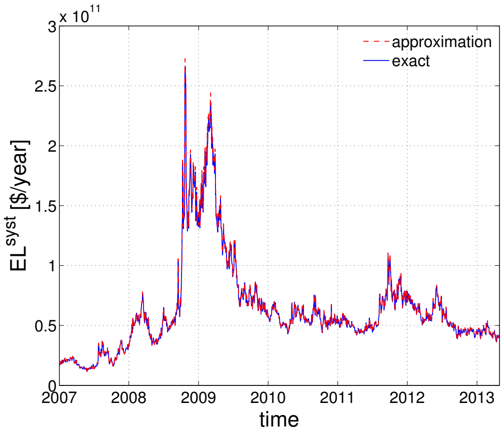


Figure 5.1: Approximation for $\mathrm{EL}^{\mathrm{syst}}$ in comparison to the exact result given by eq. (5.3). To allow computation in reasonable time we consider only the 15 largest Mexican banks. The approximation of eq. (5.7) is shown in red (dashed). The approximation is generally higher than the exact result (blue line). The deviation is on average less than 0.65% and not more than 3.5%.

5.2.4 Quantification of systemic risk of individual exposures

We estimate the impact of individual daily exposures on SR. In particular we compare the credit risk (expected loss) of a single exposure of a given size to its impact on SR. The expected loss (credit risk) of bank i is

$$\mathrm{EL}_i^{\mathrm{credit}}(t) = \sum_{j=1}^{b} p_j \, \mathrm{LGD}_j \, L_{ji}(t) \quad , \tag{5.8}$$

with p_j being the default probability as above, LGD_j the loss-given-default of j, and L_{ji} the exposure at default of i to j. The marginal contribution of an individual exposure, X_{kl} (matrix with precisely one non-zero element in line k and row l, quantifying the exposure between banks k and l) with respect to credit risk, is the increase in the credit risk of the bank with the additional exposure (risk taken by lender),

$$\Delta\mathrm{EL}^{\mathrm{credit}} = \sum_i \left[\mathrm{EL}_i^{\mathrm{credit}}(L_{ij} + X_{kl}) - \mathrm{EL}_i^{\mathrm{credit}}(L_{ij})\right] \quad . \tag{5.9}$$

Here $\mathrm{EL}_i^{\mathrm{credit}}(.)$ means that $\mathrm{EL}_i^{\mathrm{credit}}$ is computed from the network in the argument.

The impact of individual daily exposures on SR (marginal contribution), $\Delta\mathrm{EL}^{\mathrm{syst}}$ has been defined in Poledna and Thurner [4]. The marginal contribution of an individual exposure, X_{kl} (matrix with precisely one nonzero element for the exposure between k and l) on $\mathrm{EL}^{\mathrm{syst}}$ is the difference of total expected systemic loss,

$$\Delta\mathrm{EL}^{\mathrm{syst}} = \sum_{i=1}^{b} p_i \left[V(L_{ij} + X_{kl})\, R_i(L_{ij} + X_{kl}, C_i) \right. \\ \left. - V(L_{ij})\, R_i(L_{ij}, C_i)\right] \quad , \quad (5.10)$$

where $R_i(L_{ij} + X_{kl}, C_i)$ is the DebtRank and $V(L_{ij} + X_{kl})$ the total economic value of the liability network without the specific exposure X_{kl}. Clearly, a positive $\Delta\mathrm{EL}^{\mathrm{syst}}$ means that X_{kl} increases total SR. In general, this risk is borne by the public. If the increase in SR and credit risk of individual transactions are equal, $\Delta\mathrm{EL}^{\mathrm{syst}} = \Delta\mathrm{EL}^{\mathrm{credit}}$, a default of the exposure would only affect one of the involved parties (lender), and would not involve any third party. For transactions where $\Delta\mathrm{EL}^{\mathrm{syst}} > \Delta\mathrm{EL}^{\mathrm{credit}}$ third parties will also be affected by the default. The deviation of $\Delta\mathrm{EL}^{\mathrm{syst}} - \Delta\mathrm{EL}^{\mathrm{credit}} > 0$ is a simple and clear indicator for the existence of an incentive problem, where costs to third parties are generated by bilateral exposures.

5.3 The multiple layers of financial systemic risk

The data used for this work is derived from a database on exposures at the Banco de México, built and operated with the specific purpose of studying contagion and SR (see section 4.3.2). The present work is based on transaction data converted to bilateral exposures. The four exposure types are obtained in the following ways:

5.3.1 The deposits & loans layer

Daily exposures arise from interbank deposits & loans in local and foreign currency and from credit lines extended for settlement purposes. In the case of deposits & loans, the calculation of exposures is straightforward. Maturities and funding risk are not relevant in the context of this work because we are only concerned with the quantification of the loss-given-default of a counterparty.

Effects of funding risk and how it propagates among institutions can be found in Lee [141]. The current exposures $L_{ij}^{\alpha=4}(t)$ are calculated by adding up all deposits & loans between bank i and j. As is the case with most studies, we calculate the gross exposure instead of net exposure.

5.3.2 The security cross-holdings layer

Daily exposures also arise from cross-holding of securities between banks, securities lending, securities used as collateral, and securities trading. Cross-holding of securities between banks means that bank j holds securities issued by bank i. We again use the gross exposure because security contracts must be honored, even when the counterparty defaults. The daily cross-holdings gross exposures $L_{ij}^{\alpha=2}(t)$ are calculated by adding up all cross-holdings of securities that exist between bank i and j.

5.3.3 The derivatives layer

Daily exposures arise from the valuation of derivatives transactions, including swaps, forwards, options, and repo transactions. For the derivatives layer, for each type of derivative contract (swaps, forwards or options) between any two given banks, the contract is valuated and the resulting net exposure (at the contract level) is then calculated and assigned to the corresponding bank. Banks provide the information needed to perform a vanilla Black Scholes valuation of the derivative contracts. However, on the intra-month scale, banks themselves valuate most of the derivative contracts and Banco de México verifies the valuation methodologies at each bank's risk offices in order to guarantee proper modeling. In contrast to securities, exposures from derivatives are netted by each type of derivative contract. There are detailed international agreements on the netting procedure in the case of failure of a counterparty. This means, for instance, that options with the same underlying security are added up on each side and the exposures are then assigned to the counterparty with a positive net position. This process is replicated for each type of derivative with the same underlying security. The resulting net exposures are then added up to calculate the final exposure $L_{ij}^{\alpha=1}(t)$, arising from derivative contracts between bank i and bank j. In contrast to those of other more developed financial systems, derivatives in Mexico do not generate sizable exposures, and no exotic derivatives are traded. Sophisticated derivative strategies are only defined and executed by the parent banks of the Mexican subsidiaries.

5.3.4 The foreign exchange layer

As far as foreign exchange (FX) transactions are concerned, exposures reflect settlement risk (or Herstatt risk; the risk that a counterparty will not pay as obligated at the time of settlement). Mexican banks that are subsidiaries of internationally active banks are members of CLS (Continuous Linked Settlement) and are in a position to settle their FX transactions in a secured way. However, not all active banks in Mexico are in this situation and large exposures related to FX transactions do arise. If banks settle FX transactions between themselves by using the clearance service provided by CLS – which eliminates time differences in settlement – there is no exposure. Otherwise the exposure $L_{ij}^{\alpha=3}(t)$ includes both foreign currency receivable and foreign currency payable between bank i and bank j.

Finally, various balance sheet data on the 43 Mexican banks is also available, such as the capitalization measured at a monthly scale.

5.4 Quantification of systemic risk in the Mexican banking system

5.4.1 Visualization of the financial multi-layer network of the Mexican banking system

Figure 5.2 shows the various exposure layers of the Mexican banking network at 30 September 2013. The derivative exposure network is seen in the top layer (green), the second layer shows the exposures from security cross-holdings (yellow), the third shows foreign exchange exposures (red). The fourth layer represents the interbank deposits & loans market (blue). Nodes are shown at the same position in all layers. Node size represents the size of banks' total assets. Nodes i are colored according to their systemic impact, as measured by the DebtRank, R_i^α, in the respective layer (see section 5.2.2). Systemically important banks are red and unimportant ones green. The width of links represents the size of the exposures in the layer; link color is the same as the counterparty's node color (DebtRank). The total exposure in layers $\alpha = 2, 3, 4$, $\sum_{i,j} L_{ij}^\alpha(t) \approx 5 \times 10^{10}$ Mex\$, is similar in size. The total exposure of derivatives ($\alpha = 1$) is smaller, $\sum_{i,j} L_{ij}^1(t) \approx 1 \times 10^{10}$ Mex\$. However, the number of links is larger in this layer. Note that the data for derivative exposures also contains exposures from so-called repo transactions;

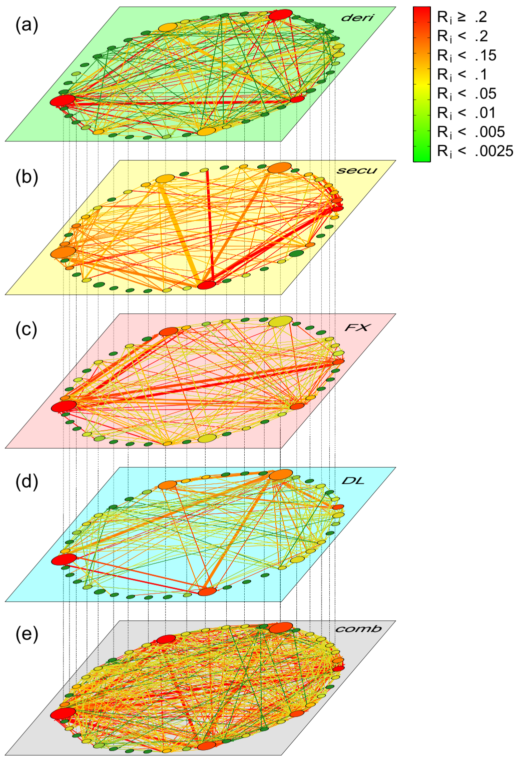


Figure 5.2: Banking multi-layer network of Mexico on 30 September 2013. (a) network of exposures from derivatives, (b) security cross-holdings, (c) foreign exchange exposures, (d) deposits & loans and (e) combined banking network $L_{ij}^{\mathrm{comb}}(t)$. Nodes (banks) are colored according to their systemic impact R_i^{α} in the respective layer (see section 5.2.2): from systemically important banks (red) to systemically safe (green). Node size represents banks' total assets. Link width is the exposure size between banks, link color is taken from the counterparty.

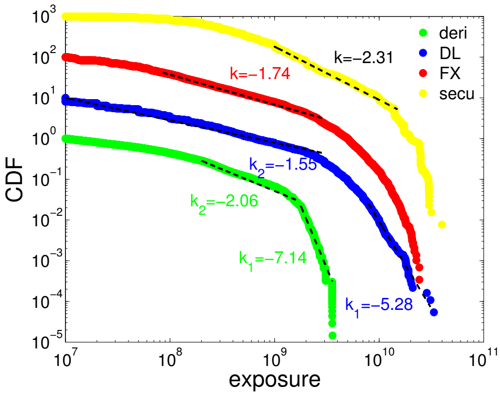


Figure 5.3: Cumulative distribution function (CDF) of the exposure sizes (in Mex$) from the different layers, deposits & loans (DL), foreign exchange exposures (FX), derivatives (deri) and security cross-holdings (secu). Data is aggregated from all days for the entire time span 2 January 2007 to 30 May 2013. Distributions are shifted vertically to avoid overlapping, by factors of 10, 100, and 1000, respectively. Clearly, the distributions are not power-laws; however, for comparison with previous literature, we report power laws fits (slopes) in several selected regions of the distributions.

the respective amounts are small (less than 2 %) because the repo involves collateral. In fig. 5.2(e) the combined exposures $L_{ij}^{\text{comb}}(t) = \sum_{\alpha=1}^{4} L_{ij}^{\alpha}(t)$ are shown.

5.4.2 The distribution of exposures in the financial multi-layer network

The cumulative distribution function (CDF) of exposure sizes for the different layers $L_{ij}^{\alpha}(t)$ is presented in fig. 5.3. Distributions are obtained by taking all exposures for every trading day in the observation period. Exposures from derivative holdings (green) are generally lower across the entire time span. Deposits & loans (blue) are more frequent in small sizes; foreign exchange exposures (red) are typically the largest positions. The distribution of exposure sizes of security cross-holdings (yellow) shows a higher variability for larger sizes compared to other layers. For the clarity of the figure, we shifted the distributions for the deposits & loans, foreign exchange exposures, and security cross-holdings by factors 10, 100, and 1000. Clearly, the observed distributions are neither power laws nor exponential functions. To formally determine

	$J_{\alpha\beta}$	$\rho^{\text{exp}}_{\alpha,\beta}$	$\rho^{\text{liab}}_{\alpha,\beta}$	$\rho^{R}_{\alpha,\beta}$
DL:Deri	0.096	0.32*	0.20	0.52
DL:Secu	0.081	0.40*	0.39	0.63
DL:FX	0.082	0.59*	0.16	0.61
Deri:Secu	0.082	0.04*	0.73*	0.19
Deri:FX	0.190*	0.56	0.85*	0.63
Secu:FX	0.094	−0.05*	0.66*	0.25

Table 5.1: Values for link-overlap (Jaccard coefficient $J_{\alpha\beta}$), and correlations of exposures (defined as $\sum_i L^{\alpha}_{ij}$) $\rho^{\text{exp}}_{\alpha,\beta}$, liabilities ($\sum_j L^{\alpha}_{ij}$) $\rho^{\text{liab}}_{\alpha,\beta}$ and DebtRank $\rho^{R}_{\alpha,\beta}$, between all possible combinations of two layers α and β, at Sep 30 2013. For the correlation of DebtRanks, R^{α}_i is calculated for the respective layers (see section 5.2.2). Significant coefficients are marked with a star.

whether the distributions expose power law tails, we conducted a standard goodness-of-fit test, which generates a p-value to quantify the plausibility of the hypothesis. We used an approach that combines a maximum-likelihood fitting method with a goodness-of-fit test, based on the Kolmogorov-Smirnov statistic and the likelihood ratios developed in Clauset et al. [142]. The p-values can be interpreted in the usual way. If $p < 0.05$, then the null hypothesis is rejected at the 5%-significance level. In that case there is sufficient statistical evidence that the distribution does not follow a power law for the identified region. The appropriate tests show the following results for each layer: Securities ($p < 0.001$), FX ($p < 0.001$), deposits & loans ($p \approx 0.0290$), and derivatives ($p < 0.001$). All p-values are below the 5%-significance level. In addition, for all exposure types, we use the goodness-of-fit-based method described in [142] to estimate the regions which can be fitted by a power. For deposits & loans and derivatives we find two regions, which can be fitted by a power. The fitted values for deposits & loans in the identified regions are $k_1 \approx -5.28$ and $k_2 \approx -1.55$ and for derivatives $k_1 \approx -7.14$ and $k_2 \approx -2.06$. For the securities layer and the FX layer we fitted only for one region, the values are $k \approx -2.31$ and $k \approx -1.74$, respectively.

5.4.3 The overlap and correlation of the layers in the financial multi-layer network

To address the question of how similar the various exposure layers are, we computed the so-called link-overlap by calculating the Jaccard coefficient $J_{\alpha\beta}$ (see paragraph 4.1.3.0.1) between two different layers α and β for all possible pairs of layers. Furthermore, we computed the correlation coefficients between exposures (weighted in-degrees, $k_j = \sum_i L_{ij}^{\alpha}$), liabilities (weighted out-degrees, $k_i = \sum_j L_{ij}^{\alpha}$) and SR (DebtRank R_i^{α}) for all banks, between all pairs of layers (see section 5.2.2). Results are collected in table 5.1. Correlation coefficients and the Jaccard coefficient are computed for the multi-layer network observed at one representative trading day (i.e., at 30 September 2013). The link-overlap (blue) between all pairs is relatively small. To test the significance of the observed link-overlap, we compare it to a null-model. For the randomized null-model we preserved the interbank assets or exposures of each bank (weighted in-degrees of L_{ij}^{α}) and rewired the exposure to a random bank, similar to the method used by Maslov and Sneppen [143]. Rewiring the interbank exposure to a random counterparty means that the liabilities (weighted out-degrees of L_{ij}^{α}) are not preserved. Therefore, total assets and equity capital of each bank remain unchanged. Note that it is not possible to preserve (weighted) in- and out-degree at the same time. We find that the link-overlap practically coincides with the null-model, meaning that if banks have business relations in one market, it is not more likely that they also interact in other markets. Only the link-overlap between derivatives and foreign exchange shows slightly higher levels than the null-model, indicating that if two banks have exposure in securities the probability of having one in FX is marginally higher than in the null-model.

High correlation coefficients $\rho_{\alpha,\beta}^{\mathrm{exp}}$ (see paragraph 4.1.3.0.2) between total exposures of banks indicate that banks that have high (low) exposure in layer α also have high (low) exposure in layer β. Correlation coefficients $\rho_{\alpha,\beta}^{\mathrm{exp}}$ close to zero mean that total exposures of banks are not correlated in layer α and β. The correlations for liabilities of banks $\rho_{\alpha,\beta}^{\mathrm{liab}}$ and $\rho_{\alpha,\beta}^{\mathrm{R}}$ are interpreted in the same way. We find in table 5.1 that $\rho_{\alpha,\beta}^{\mathrm{exp}}$ is close to zero for the pair (derivatives : securities), meaning that they are almost uncorrelated. We find negative correlations for the layer (securities : FX), meaning that exposures that are high in securities imply small exposures in FX and vice versa. Correlations for liabilities $\rho_{\alpha,\beta}^{\mathrm{liab}}$ are high for the pairs (derivatives : securities), (derivatives : FX) and (securities : FX), and low for (DL : derivatives) and (DL : FX). Compared to the null-model, correlation coefficients $\rho_{\alpha,\beta}^{\mathrm{exp}}$ for all pairs are significant, with the single exception of the pair (derivatives : FX). Here $\rho_{\alpha,\beta}^{\mathrm{exp}}$ coincides with the null-model. Correlations for liabilities $\rho_{\alpha,\beta}^{\mathrm{liab}}$ are significant for the pairs (derivatives : securities), (derivatives : FX) and (securities : FX). Finally, the correlation of SR at the bank level is $\rho_{\alpha,\beta}^{\mathrm{R}} > 0.5$ for all pairs except for (derivatives : securities) and (securities : FX) where correlations are small. These latter pairs are different in the sense that their total exposures and systemic impact are practically uncorrelated. All the other layers are strongly correlated. Note that we cannot compare correlation results of SR at the bank level with the null-model because it is impossible to preserve (weighted) in- and out-degrees at the same time.

5.4.4 Classical network statistics of the financial multi-layer network

We present classical network statistics for each of the layers, as well as for the combination of all layers. In table 5.2 we present the evolution of densities of different layers and the correlations between the degrees and weights of nodes across different pairs of layers. Values are presented as an annual average from 2007 until 2013.

In the first part of table 5.2 we show the evolution of network density for all layers combined as well as for each individual layer. The densities for the derivatives layer, deposits & loans and FX remain stable from 2007 to 2013. Densities of the securities layer and for all layers combined increase every year in the observation period.

In the second part of table 5.2 we show the evolution of degree correlations between layers. For every pair of layers we show the degree correlation (All), the in-degree correlation (In), and the out-degree correlation (Out). It is important to distinguish between incoming and outgoing links because they have a different economic interpretation. The former can be thought of as a form of funding or trust relationship that many banks have with one bank; the latter is related to the concept of exposure.

The third part of table 5.2 shows the evolution of weight correlations between layers. For every pair of layers we show the weight correlation (All), the in-weight correlation (In), and the out-weight correlation (Out).

An extensive display of stylized facts of the Mexican banking system network can be found in Martínez-Jaramillo et al. [131]. A more in-depth multiplex empirical analysis for a database similar to the one used here can be found in Molina-Borboa et al. [144].

5.4.5 How much does a financial crisis cost?

Figure 5.4(a) shows the SR-profile for the combined exposures R_i^{comb} (line) and stacked for different layers $\hat{R}_i^{\alpha}$ (colored bars) for 30 September 2013.

		2007	2008	2009	2010	2011	2012	2013
Density								
	DL	0.062(4)	0.064(3)	0.062(2)	0.063(4)	0.075(3)	0.074(3)	0.076(3)
	FX	0.064(5)	0.06(2)	0.06(2)	0.08(2)	0.07(1)	0.08(2)	0.08(1)
	secu	0.02(1)	0.029(3)	0.029(3)	0.039(6)	0.06(5)	0.068(4)	0.07(6)
	deri	0.1(1)	0.09(2)	0.09(2)	0.11(1)	0.098(8)	0.098(8)	0.098(10)
	comb	0.21(1)	0.25(2)	0.24(2)	0.28(2)	0.32(2)	0.33(1)	0.34(1)
Pair-wise degree correlation								
DL:Secu	All	0.68(7)	0.68(5)	0.63(6)	0.61(5)	0.64(4)	0.59(4)	0.51(4)
	In	0.46(8)	0.49(8)	0.43(8)	0.42(8)	0.49(5)	0.46(6)	0.38(6)
	Out	0.53(7)	0.58(6)	0.49(8)	0.46(6)	0.49(4)	0.36(6)	0.31(4)
DL:FX	All	0.54(6)	0.47(7)	0.39(6)	0.4(6)	0.35(6)	0.36(7)	0.38(7)
	In	0.49(6)	0.4(7)	0.38(7)	0.4(6)	0.36(6)	0.37(7)	0.39(7)
	Out	0.45(6)	0.35(8)	0.17(6)	0.21(6)	0.17(7)	0.15(6)	0.17(6)
DL:Deri	All	0.32(5)	0.24(7)	0.2(8)	0.13(5)	0.25(7)	0.29(6)	0.27(7)
	In	0.24(6)	0.19(6)	0.25(8)	0.2(6)	0.34(7)	0.35(7)	0.35(7)
	Out	0.2(5)	0.11(7)	0(6)	-0.04(4)	0.13(7)	0.1(5)	0.08(6)
Secu:FX	All	0.68(7)	0.56(6)	0.52(8)	0.53(7)	0.49(5)	0.46(5)	0.46(6)
	In	0.53(8)	0.46(7)	0.46(6)	0.49(8)	0.45(7)	0.4(7)	0.35(7)
	Out	0.56(8)	0.5(6)	0.3(1)	0.32(7)	0.33(7)	0.29(6)	0.33(6)
Secu:Deri	All	0.49(7)	0.47(7)	0.4(1)	0.24(5)	0.32(5)	0.3(5)	0.2(6)
	In	0.48(7)	0.41(9)	0.5(1)	0.24(5)	0.44(8)	0.5(5)	0.35(9)
	Out	0.27(7)	0.32(7)	0.22(8)	0.13(6)	0.17(8)	0.04(5)	0.03(6)
FX:Deri	All	0.7(5)	0.6(7)	0.57(7)	0.51(5)	0.57(6)	0.57(5)	0.58(6)
	In	0.66(6)	0.57(8)	0.57(7)	0.51(6)	0.59(7)	0.6(7)	0.59(7)
	Out	0.67(6)	0.58(6)	0.54(7)	0.48(6)	0.58(6)	0.56(6)	0.58(7)
Pair-wise weight correlation								
DL:Secu	All	0.7(2)	0.79(9)	0.8(1)	0.7(1)	0.8(1)	0.78(8)	0.6(1)
	In	0.6(3)	0.7(2)	0.7(2)	0.4(2)	0.6(2)	0.6(1)	0.4(1)
	Out	0.4(2)	0.4(2)	0.4(3)	0.6(2)	0.6(2)	0.7(1)	0.6(1)
DL:FX	All	0.6(2)	0.5(2)	0.7(2)	0.5(2)	0.5(1)	0.5(2)	0.4(1)
	In	0.5(2)	0.5(2)	0.6(2)	0.5(2)	0.5(2)	0.5(2)	0.4(2)
	Out	0.5(2)	0.4(2)	0.4(2)	0.3(2)	0.3(2)	0.3(2)	0.3(2)
DL:Deri	All	0.82(9)	0.7(1)	0.69(9)	0.6(2)	0.62(9)	0.54(7)	0.59(9)
	In	0.6(2)	0.6(1)	0.5(2)	0.5(2)	0.7(2)	0.5(1)	0.4(2)
	Out	0.6(2)	0.4(2)	0.4(2)	0.3(2)	0.2(1)	0.2(1)	0.2(1)
Secu:FX	All	0.5(2)	0.5(1)	0.6(2)	0.56(10)	0.5(1)	0.4(1)	0.3(1)
	In	0.5(2)	0.5(2)	0.7(2)	0.7(1)	0.6(1)	0.5(1)	0.5(1)
	Out	0.3(2)	0.2(1)	0.2(2)	0.09(8)	0.09(9)	0.03(10)	0.03(7)
Secu:Deri	All	0.6(2)	0.6(1)	0.68(10)	0.63(8)	0.67(7)	0.54(3)	0.4(1)
	In	0.6(2)	0.7(1)	0.6(1)	0.7(2)	0.8(2)	0.88(4)	0.8(1)
	Out	0.4(2)	0.3(1)	0.08(5)	0.06(3)	0.08(5)	-0.02(4)	0.05(5)
FX:Deri	All	0.8(1)	0.7(1)	0.7(1)	0.7(1)	0.7(1)	0.7(1)	0.78(8)
	In	0.7(2)	0.6(2)	0.5(2)	0.6(2)	0.6(2)	0.5(2)	0.6(1)
	Out	0.6(1)	0.6(2)	0.6(1)	0.6(2)	0.6(1)	0.6(1)	0.7(1)

Table 5.2: Classical network statistics for the multi-layer network. In the first part we show the evolution of network density for all layers combined, as well as for each individual layer. In the second part we show the pair-wise degree correlation, and in the third part the pair-wise weight correlation. Values are presented as an annual average from 2007 until 2013. The number in parentheses is the standard deviation referred to the corresponding last digits of the quoted result.

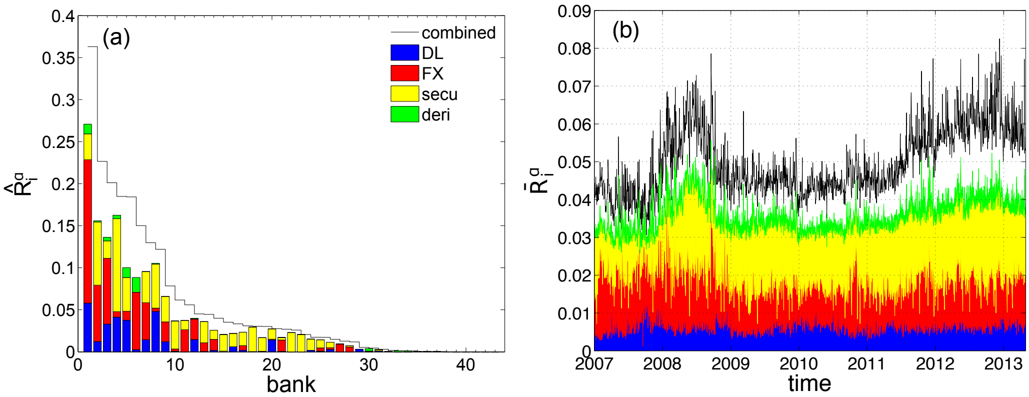


Figure 5.4: (a) SR profile for the different layers. Normalized DebtRank $\hat{R}_i^\alpha$ (see section 5.2.2) from different layers are stacked for each bank. Banks are ordered according to their DebtRank in the combined network from all layers (line). (b) Time series for the average DebtRank $\bar{R}^\alpha(t) = \frac{1}{b}\sum_{i=1}^{b} \hat{R}_i^\alpha(t)$ for all layers from 2 January 2007 to 30 May 2013. The black line shows the average DebtRank for all layers combined $\bar{R}^{\text{comb}}(t) = \frac{1}{b}\sum_{i=1}^{b} R_i^{\text{comb}}(t)$.

Clearly, individual banks have different SR contributions from the different layers, reflecting their different trading strategies. A number of smaller banks has systemic impact in the securities market only. The SR contribution from the interbank (deposits & loans) and the derivative markets is clearly smaller than the contributions from the foreign exchange and securities markets. The systemic impact of the combined layers (line) is always larger than the sum of the layers separately, $R_i^{\text{comb}} > \sum_\alpha \hat{R}_i^\alpha$.

Figure 5.4(b) shows the daily *average DebtRank* $\bar{R}$ from January 2007-March 2013 for the different layers (stacked) and from the combined networks (line). As in fig. 5.4(a) the combined systemic impact is always larger than the combination of all layers separately. Note that the combined average DebtRank $\bar{R}^{\text{comb}}$ increases about 50% from roughly 1.7 before the financial crisis of 2007-2008 to about 2.6 in 2013. The contributions of the individual exposure types are more or less constant over time. The interbank (deposits & loans) and derivative markets have smaller average DebtRank contributions than foreign exchange or securities. The derivatives market gained importance in Mexico after 2009. Note the relative SR increase of securities at the beginning of the subprime crisis (Dec 2007) and the subsequent decrease shortly before the collapse of Lehman Brothers. There is a marked peak in foreign exchange exposure two days after Lehman Brothers filed for chapter 11 bankruptcy protection.

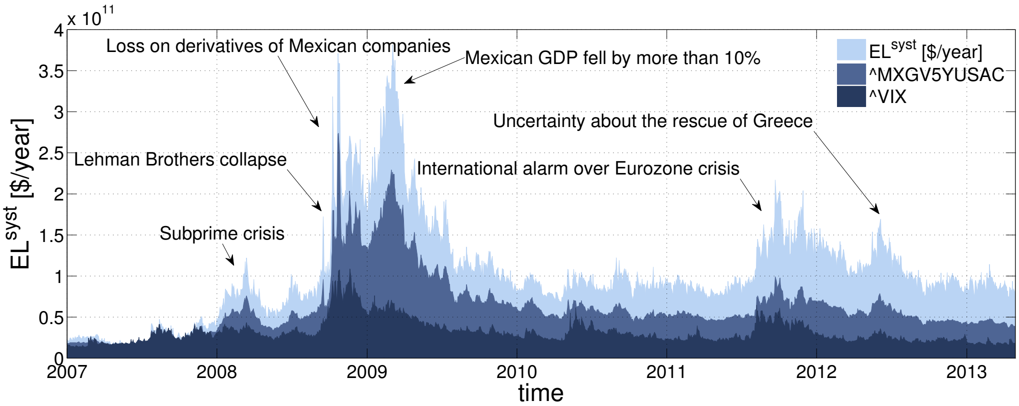


Figure 5.5: Expected systemic losses $\mathrm{EL}^{\mathrm{syst}}$ in Mex$ per year, in comparison to the volatility index VIX and the CDS spreads of 5-year Mexican government bonds in USD (MXGV5YUSAC). To allow comparison the MXGV5YUSAC and the VIX are scaled such that the data points coincide on 2 January 2007. Several historical events are marked. Market-based indices relax fast to pre-crisis levels, whereas $\mathrm{EL}^{\mathrm{syst}}$ does not, indicating that the expected systemic losses are indeed driven to a large extent by network topology and are consistently underestimated by the market. Expected losses in 2013 are about four times higher than before the crisis.

Figure 5.5 shows the daily development of EL^{syst} for Mexico from 2007-2013. In Mexico there are no CDS spreads of banks available, and ratings are only made available for the purpose of issuing securities by banks. This makes it difficult to derive individual default probabilities for banks. As an alternative we approximate the default probabilities for banks with sovereign default probabilities. Typically banks' strategies involve having a rating no better than the sovereign where they are registered. In general, Mexican banks are well-capitalized, especially the large subsidiaries of foreign banks. It is for this reason that we believe it to be justifiable to use sovereign default probabilities as a proxy for all banks. As a reference we use the 5-year Mexican government bonds in USD (MXGV5YUSAC) and assume a 40% recovery rate, which is the standard market convention for the quotation of CDS contracts. The short-term volatility of the expected loss is mainly driven by international events. As is the case with other credit risk models, for example models for credit default swaps [145, 146], we assume that default events and recovery rates are mutually independent. In fig. 5.5 we highlight several historical events and show the volatility index VIX and the CDS spreads scaled such that the data points coincide on 2 January 2007. We see that both the volatility index and the CDS spreads return quickly to pre-crisis levels, whereas EL^{syst} clearly does not. This indicates that markets drastically underestimate SR in the system – the expected systemic losses in 2013 are about a factor four higher than before the crisis.

5.4.6 What is the impact of individual daily exposures on systemic risk?

In fig. 5.6 we compare the marginal contribution of individual exposures on SR and credit risk. Every one of the ca. 500,000 individual exposures between banks across the entire time period is represented by a data point. The different layers are distinguished by colors. We immediately observe that $\Delta EL^{syst} > \Delta EL^{credit}$ for the vast majority of transactions. We made sure that this finding could not be explained by the exposure size relative to equity capital or by capital ratios (not shown). This clearly demonstrates that marginal contributions from individual liabilities depend not only on the two parties involved, but also on the conditions of all nodes in the network. Note that small and medium-size liabilities can have SR contributions that vary by three orders of magnitude. Deposits & loans and derivatives show the lowest variability, whereas for foreign exchange the variability is a bit higher. Derivatives show clusters of transactions with particularly high SR

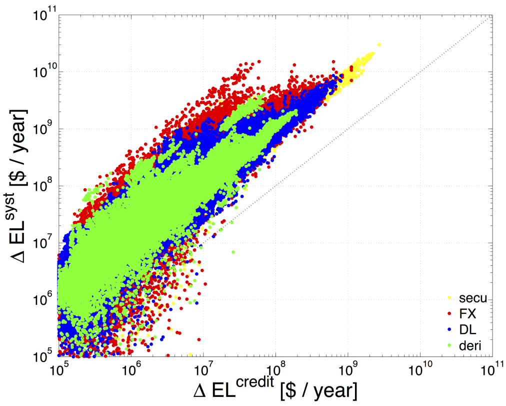


Figure 5.6: Marginal increase of expected systemic loss, $\Delta\mathrm{EL}^{\mathrm{syst}}$, versus increase of credit risk, $\Delta\mathrm{EL}^{\mathrm{credit}}$, for individual exposures between institutions. Every data point represents an individual interbank liability L_{ij}^{α} on a given layer and given day. Data is aggregated from all banks over all days from 2 January 2007 to 30 May 2013. Exposures/liabilities lower than 10 million Mex$ are not shown. Note that $\Delta\mathrm{EL}^{\mathrm{syst}} > \Delta\mathrm{EL}^{\mathrm{credit}}$ meaning that defaults of exposures do not only affect the "lending" party but also involve third parties.

contributions for the corresponding liability size. Exposures from security cross-holdings have the highest contributions to SR.

Note that in some cases $\Delta\mathrm{EL}^{\mathrm{syst}} < \Delta\mathrm{EL}^{\mathrm{credit}}$, meaning that a few exposures have an SR reducing effect on the network. Although counterintuitive, removing a link can change the topology of a network in such a way that overall SR increases even if the total exposure of the system is decreased.

To exclude the possibility of this effect arising as an artifact of the measure, we conducted computer simulations with the model introduced in Poledna and Thurner [4]. We modified (eq. (5.10)) to always predict an increase of SR equal or larger to the overall increase of exposure in the system, i.e.,

$$\Delta'\mathrm{EL}^{\mathrm{syst}} = \max\left(\Delta\mathrm{EL}^{\mathrm{syst}}, \Delta\mathrm{EL}^{\mathrm{credit}}\right) \quad . \tag{5.11}$$

In computer simulations we used (eq. (5.10)) and (eq. (5.11)) to estimate the increase of SR in the simulated financial system. Results indicate that the unmodified version of eq. (5.10) predicts losses due to SR slightly better than in the modified version.

5.5 Implications for economics and society

To a large extent SR is related to the topologies of a collection of financial exposure networks (multi-layer network). In this chapter we provide, to our knowledge, the first complete empirical picture of network-based SR in a national, system-wide context. By analyzing SR contributions from four exposure layers of the interbank network (derivatives, security cross-holdings, foreign exchange and the interbank market of deposits & loans) we show that by relying on the single layer of deposits & loans – as done in previous studies – one drastically underestimates SR in the system, missing about 90% of the total SR. We demonstrate that the exposures related to the cross-holding of securities and the exposures arising from FX transactions are crucially important components of the SR of a country. These exposures are almost never taken into consideration as part of contagion studies, when in fact they need to be included in order to provide a more complete picture of the risks faced by the financial system.

On a national level we suggest a SR-profile that captures the SR contributions from all financial institutions in a country across the various exposure layers. It is straightforward to use the SR profile to introduce a system-wide systemic risk measure (i.e., the average DebtRank, which takes all exposure layers into account). The average DebtRank captures the contribution of the various network topologies and can be computed on a daily scale. Interestingly, the SR of the combined exposure network is higher (increasingly so over time) than the sum of SR from the four layers. This points to the non-linearity of the definition of the systemic risk measure. The root cause for this non-linearity is the propagation of shocks to financial institutions between the layers. For example, a loss from trading derivatives can spill over to other markets. This non-linear effect was seen in a different context before in Montagna and Kok [88]. If financial institutions were restricted to a particular segment of the market (e.g., some investment banks only trading securities, while other banks only engage in interbank lending), the non-linearity in the aggregation of the layers would disappear. This evidence could provide a further argument for a structural reform of the banking system, aiming at a separation or restriction of certain trading activities, as suggested in several proposals [147, 148]. Although the idea of these proposals is to ring-fence deposit banks to safeguard against riskier banking activities, we believe that a structural separation of trading actives to separate legal entities would also reduce SR in general.

The DebtRank, in combination with estimates of default probabilities of institutions, allows us to define a novel index, $\mathrm{EL}^{\mathrm{syst}}$, the *expected systemic losses* within a financial economy. The index quantifies the total losses of a potential cascading event at any point in time, provided that no bailouts are taking place at that time. This makes it possible to quantify the costs originating from SR in pesos/euros/dollars per year, provided that governments do not employ a resolution mechanism (such as a bailout) for troubled banks. The expected systemic loss further enables us to compare expected costs for bailouts with the expected systemic loss, so that decisions for bailouts can be based on quantitative, transparent, and rational grounds. Finally, the expected systemic loss $\mathrm{EL}^{\mathrm{syst}}$ can be used to compare economies and to indicate the SR-reducing performance of policy interventions.

We find that financial markets systematically underestimate SR. When we compare the expected systemic loss with the volatility index (VIX) and the CDS spreads of 5-year Mexican government bonds, it becomes clear that expected systemic loss follows several features of these market risk indicators. However, while the VIX returned to pre-crisis levels and the spreads have doubled since the crisis, the expected systemic loss has quadrupled since 2007. This means that the potential direct costs for a cascading failure in Mexico would be four times higher now than before the crisis.

In recent years various studies using multiplex network analysis have demonstrated that trying to understand a system from a single network layer can lead to a fundamentally wrong understanding of the entire system and that the dynamics of multiplex systems can be very different from single-layer networks [133, 134, 135]. The multi-layer analysis of financial networks points in a similar direction, namely, that there might be much higher SR levels present in the financial system than previously anticipated or than markets assume. There are two reasons why we still might underestimate SR. First, we do not include other potentially important sources of contagion, such as the network of overlapping portfolios and funding liquidity risk. The inclusion of more network layers is the subject of future studies. Second, in this work we assume that default events and recovery rates are mutually independent, which does not hold, in practice, for a number of reasons. In conclusion, true values of SR might be still significantly higher.

Chapter 6

Understanding systemic risk from overlapping portfolios and the leverage cycle

6.1 The leverage cycle and its implication on systemic risk

The recent crash in home and mortgage prices, and the ensuing global recession, has brought forth numerous proposals for the regulation of leverage. The trouble is that many of these proposals ignore the mechanism of the leverage cycle, and thus might unwittingly do more harm than good.

Leverage is defined as the ratio of assets held to wealth. A homeowner who buys a house for \$100 by putting down \$20 of cash and borrowing the rest is leveraged 5 to 1. One reason why leverage is important is that it measures how sensitive the investor is to a change in asset prices. In the case of the homeowner, a \$1 or 1% decline in the house price represents a 5% loss in his wealth, since after he sells the house and repays the \$80 loan he will only have \$19 out of his original \$20 of capital. Limiting leverage therefore seems to protect investors from themselves, by limiting how much they can all lose from a 1% fall in asset prices. Basle II[1] effectively puts leverage limits, *through rules for eligible financial collateral*, on loans banks can give to investors, and furthermore it ties the leverage restriction to the volatility of asset prices: if asset prices become more likely to change by 2% instead of 1%, then Basle

[1]Note that we do not refer here to the minimum leverage ratio introduced in Basle III.

II curtails leverage even more. At first glance this seems like good common sense.

The leverage cycle, however, does not arise from a once and for all exogenous shock to asset prices whose damages to investors can be limited by curtailing leverage. On the contrary, the leverage cycle is a process crucially depending on the heterogeneity of investors. Some investors are more optimistic than others, or more willing to leverage and buy than others. When the market is doing well these investors will do well and via their increased relative wealth and their superior adventurousness, a relatively small group of them will come to hold a disproportionate share of the assets. When the market is controlled by a smaller group of agents who are more homogeneous than the market as a whole, their commonality of outlook will tend to reduce the volatility of asset prices. But this will enable them, according to the Basle II rules, to leverage more, which will give them a still more disproportionate share of the assets, and reduce volatility still further. Despite the leverage restrictions intended from Basle II, the extremely low volatility still gives room for very high leverage.

At this point some exogenous bad luck that directly reduces asset prices will have a disproportionate effect on the wealth of the most adventurous buyers. Of course they will regard the situation as an even greater buying opportunity, but in order to maintain even their prior leverage levels they will be forced to sell instead of buying. At this point volatility will rise and the Basle II lending rules will force them to reduce leverage and sell more. The next class of buyers will also not be able to buy much because their access to leverage will also suddenly be curtailed. The assets will cascade down to a less and less willing group of buyers. In the end, the price of the assets will fall not so much because of the exogenous shock, but because the marginal buyer will be so different from what he had been before the shock. Thus we shall show that in some conditions, Basle II not only would fail to stop the leverage build up, but it would make the deleveraging crash much worse by curtailing all the willing buyers simultaneously. The policy itself creates systemic risk.

We shall also see that another apparently sensible regulation can lead to disaster. Common sense suggests it would be safer if the banks required funds to hedge their positions enough to guarantee they can pay their debts before they could get loans. The trouble with this idea is that when things are going well, the most adventurous leveragers will again grow, thereby lowering volatility. This lower volatility will reduce their hedging costs, and enable them to grow still faster and dominate the market, reducing volatility and hedging costs still more. Bad luck will then disproportionately reduce the wealth of the most enthusiastic buyers. But more importantly, it will increase volatility and thus hedging costs. This will force further selling by the most enthusiastic buyers, and limit the buying power of the next classes of potential owners. In just the same way as Basle II, the effort to impose common sense regulation of leverage can create bigger crashes.

In recent years a variety of studies including [27], [28], [29], [30], [31], and [32] have made it clear that deleveraging can cause systemic financial instabilities leading to market failure, as originally discussed by [26]. The specific problem is that regulatory action can cause synchronized selling, thereby amplifying or even creating large downward price movements. In order to stabilize markets a variety of new regulatory measures have been proposed to suppress such behavior. But do these measures really address the problem?

In this chapter we focus on the systemic risk component of overlapping portfolios. By systemic risk here we mean the default of financial institutions generated by the internal dynamics of the financial system. Such defaults are typically synchronized and in more serious cases involve the default of a substantial number of agents. Our example here is simple, as there is only one risky asset. Contagion is transmitted between agents when they buy or sell the asset, and as we will see, the use of leverage can lead to market crises. A key point in this study is that crises emerge endogenously, under normal operation of the model – there are long periods where the market is relatively quiet, but due to the build up of leverage, the market becomes more sensitive to small fluctuations (which would at other times have negligible effect).

Of particular interest here are leverage constraints, which are a significant part of financial regulation. These constraints are implemented in numerous ways, most influential in the form of capital adequacy rules in the Basle II framework and as margin requirements and debt limits in the Regulations T, U, and X of the Federal Reserve System. Margin requirements were established in the wake of the 1929 stock market crash with the belief that margin loans led to risky investments resulting in losses for lenders [149]. Fortune [150] discusses the regulation, historical background, accounting mechanics and economic principles of margin lending according to Regulations T, U, and X.

In comparison to straightforward leverage constraints, the Basle II capital adequacy rules classify and weight assets of banks according to credit risk. Banks regulated under the Basle II framework are required to hold capital equal to 8% of risk-weighted assets. A recent case study of the Bank of Canada discusses unweighted leverage constraints as a supplement to existing risk-weighted capital requirements [151]. The second of the Basle II Accords (Basle II) capital adequacy regulations added a significant amount of complexity and sophistication to the calculation of risk-weighted assets. In particular, banks are encouraged to use internal models, such as value-at-risk (VaR), to determine the value of risk-weighted assets according to internal estimations. In a nontechnical analysis of the Basle II rules, Balin [63] provides an easy accessible analysis of both the Basle I and Basle II framework.

Lo and Brennan [152] provide an extensive overview of leverage constraints, pointing out that regulatory constraints on leverage are generally fixed limits that do not vary over time or with changing market conditions, and suggest that from a micro prudential perspective fixed leverage constraints result in large variations in the level of risk. Recent studies of central banks also conclude that current regulatory leverage constraints are inadequate [153, 154]. From a macro prudential perspective internal estimations of banks appear to be cyclically biased in determining the value of risk-weighted assets, contributing to a pro cyclical increase in global leverage [151]. Keating et al. [155] and Daníelsson [156] have also argued that the Basle II regulations fail to consider the endogenous component of risk, and that the internal models of banks can have destabilizing effects, inducing crashes that would otherwise not occur.

Computational agent-based models have gained popularity in economic modeling over the last decades and are able to reproduce some empirical features of financial markets that traditional approaches cannot replicate[157]. An advantage of this approach is the ability to implement institutional features accurately and to be able to simulate any model setup, without the constraints of analytic tractability. An extensive review of financial multi-agent models can be found in [158] and [159]. [158] has focused more on models with many types of agents and [159] concentrating more on models with a few types of agents and the effects of heterogeneous strategies.

In this chapter we use an agent-based financial market model introduced by Thurner et al. [31] to test the performance of several credit regulation policies. The model introduced by Thurner et al. [31] will be used as a baseline. In this chapter, the model is extended to allow short selling and to incorporate different regulation policies. The use of this simulation model allows us to explicitly implement and test any given regulatory policy. We test three different cases: (1) An unregulated market, (2) the Basle II framework and (3) a hypothetical regulatory policy in which banks completely hedge against possible losses from providing leverage (while charging their clients the hedging costs). We find that when leverage is high both of the regulatory schemes fail to guard against systemic financial instabilities, and in fact result in even higher rates of default than no regulation at all. The reason for this is that both regulatory policies compel investors to deleverage just when this is destabilizing, triggering failures when they would otherwise not occur.

Agent-based models have often been criticized for making arbitrary assumptions, particularly concerning agent decision making. We address this problem here by keeping the model simple and making a minimum of behavioral assumptions. There are four types of investors:

1. *Fund managers* are perfectly informed value investors that all see the same perfect valuation signal. They buy when the market is underpriced and sell when it is overpriced. Fund managers are risk-neutral.

2. *Noise traders* are inattentive value investors. They buy or sell when the market is under or over priced, but do so less efficiently than the fund managers. Noise traders are risk-neutral.

3. *Banks* loan money to the fund managers to allow them to leverage. Banks are risk-averse, though the extent to which this is true differs depending on the regulator scheme.

4. *Fund investors* place or withdraw money from the fund managers based on a historical average of each fund's performance.

The fund managers, which are the primary focus of this article, are heterogeneous agents, i.e. there are multiple funds with different levels of aggression. In contrast, the other three types are representative agents, i.e. there is a single noise trader, a single bank, and a single fund investor. The primary function of the noise traders is to provide a background price series to generate opportunities for the fund investor; the function of the fund investors is to guarantee that the price dynamics can be run in a steady state without the fund managers becoming infinitely wealthy. The bank is there to lend money to the funds, but it is a backdrop – the bank is infinitely solvent. (It is nonetheless useful to examine welfare measures, such as the losses to the bank, rate of default on loans, etc.)

The postulated behaviors of each type of agent are reasonably generic, and in some cases, such as for the banks, we are merely codifying behaviors that are essentially mechanical and legally mandated by the terms of contractual agreement or regulation. Most importantly, our results are relatively insensitive to assumptions. The fact that this is a simulation model has the important advantage of allowing us to quantitatively and explicitly evaluate any regulatory scheme. This model is useful because it can incorporate more realism than a typical stylized equilibrium model [160, 161, 162, 163]. This joins a growing class of agent-based models for testing economic policies that attempt quantifiable, reproducible and falsifiable results, whose parameters are – at least in principle – observable in reality. Recent studies that use agent-based models for testing economic policies include Demary [164], Haber [165], Westerhoff [166], Westerhoff and Franke [167], Kerbl [168] and Hermsen [169].

In section 6.2, following Thurner et al. [31] we present the model that serves as the baseline for comparison of regulatory schemes. In section 6.3 the modifications necessary to implement the regulatory measures are explained. Section 6.4 presents simulation results comparing both the Basle II-type regulation and the full perfect-hedge regulation schemes under various leverage levels in the financial system. In section 6.5 we conclude, discussing why Basle II-type systems – even in their most ideal form – destabilize the market just when stability is most needed, i.e. in times of high leverage levels in the system. At the heart of this problem are synchronization effects of financial agents in time of stress.

6.2 A simple model for the leverage cycle

The baseline model represents a market that is unregulated except for a maximum leverage requirement. It is an agent-based model with four different types of agents as described in [31]. There is only a single asset, without dividends and consumption, and investors are given a choice between holding the asset or holding cash. Prices are formed via market clearing. In the subsequent paragraphs we give an overview of each type of agent, and then in the remainder of this section we describe their behavior in more detail.

In fig. 6.1 we show a schematic structure of the model. The first type of agents are *fund managers*, e.g. hedge funds or proprietary trading groups. They are value investors who "buy low and sell high". They use a strategy that translates a mispricing signal into taking a long position (buying a positive quantity of the asset) when the asset price $p(t)$ at time t is below a perceived fundamental value V. We generalize the model of Thurner et al. by also allowing them to take a short position when the asset is over-priced, i.e. one for $p(t) > V$. The demand of fund managers is denoted by $D_h(t)$, where the subscript h refers to the fund manager. The fund managers are heterogeneous agents who differ in the aggressiveness with which they respond to buy and sell signals.

The second type of agent is a representative *noise trader*. This agent can

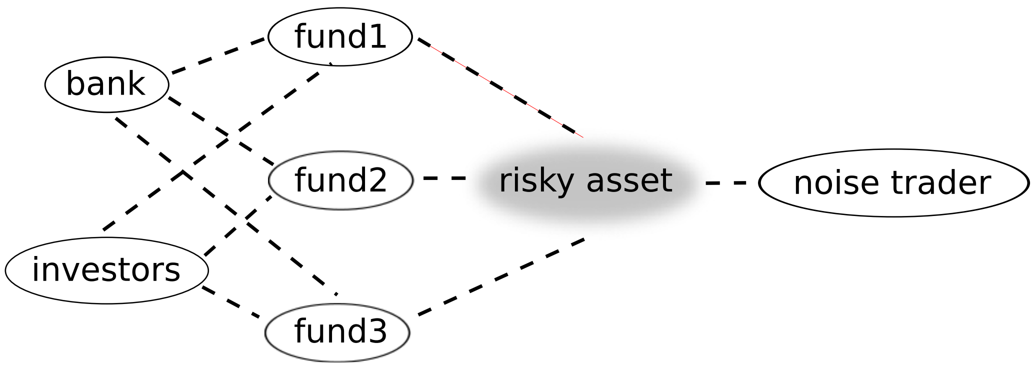


Figure 6.1: Schematic structure of the model: Fund managers buy a single risky asset when it is underpriced and sell when it is overpriced. Noise traders also buy or sell when the market is under or over priced, but do so less efficiently than the fund managers – the noise traders and fund managers have the same notion of value. A representative bank loans money to the fund managers to allow them to leverage. In the Basle II and the perfect-hedge scheme fund managers pay fees for receiving loans, see eq. (6.18) and eq. (6.19). Investors place or withdraw money from the funds based on their historical performance. Funds are heterogeneous based on the aggression of their investment strategy; more aggressive funds tend to use more leverage. For fund manager profits see fig. 6.8(c). In the model no actual fees are paid. The plot corresponds to a hypothetical situation, which is certainly correct for small hedge funds.

be thought of as a weakly informed value investor, who has only a vague concept of the fundamental price, and thus buys and sells nearly at random, with just a small preference that makes the price weakly mean-revert around V. The demand of noise traders at time t is $D_n(t)$. The noise trader is a representative agent, representing the pool of weakly-informed investors that cause prices to revert toward value.

The third type of agent is a *bank*. Fund managers can increase the size of their long positions by borrowing from the bank by using the asset as collateral. The bank limits lending so that the value of the loan is always (substantially) less than the current price of the assets held as collateral. This limit is called a minimum margin requirement. In case the asset value decreases so much that the minimum margin requirement is no longer sustained, the bank issues a margin call and the fund managers who are affected must sell assets to pay back their loans in order to maintain minimum margin requirements. This happens within a single time step in the model. This kind of transaction is called margin trading and has the effect of amplifying any profit or loss from trading. If large price jumps occur and fund managers cannot repay the loan even by selling their complete portfolio, they default. In the baseline model, for simplicity interest rates for loans are fixed to zero and the bank sets a fixed minimum margin requirement, denoted by $\lambda_{\max}$.

The fourth type of agent is a representative *fund investor* who places or withdraws money from a fund according to performance. This agent should be viewed as a representative agent characterizing all investors, both private and institutional, who place money with funds that use leverage. The amount invested or redeemed depends on recent historical performance of each fund compared to a fixed benchmark return r_b. Successful fund managers attract additional capital, unsuccessful ones lose capital.

6.2.1 Price formation and its role for interactions

At each time step t asset prices $p(t)$ are formed via market clearing by equating the sum over the demand of the fund managers $D_h(t)$ and the noise traders $D_{\mathrm{n}}(t)$ to the fixed total supply N of the asset, which represents the number of issued shares. The market clearing condition is

$$D_{\mathrm{n}}(t) + \sum_h D_h(t) = N. \tag{6.1}$$

At every time step the fund managers must decide how much of their total wealth $W_h(t)$ they are going to invest. The wealth of a fund manager is the

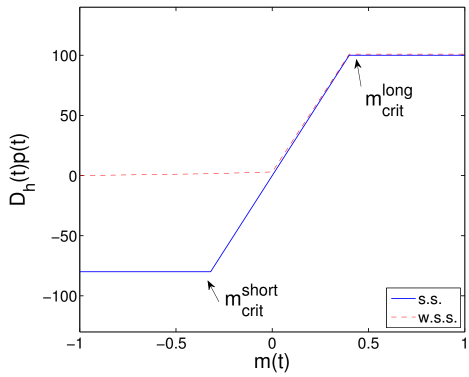


Figure 6.2: Demand function $D_h(t)p(t)$ of a fund manager as a function of the mispricing signal $m(t) = V - p(t)$. If the asset is underpriced the fund manager starts buying more and more assets as the price decreases, until the maximum margin requirement (leverage limit) is hit at $m = m_{\text{crit}}$. Above this mispricing the demand remains flat. If short selling is banned (dashed line) the fund manager holds no assets if the asset is overpriced, whereas when short selling is allowed (solid line) the fund manager takes a negative position on the asset when it is overpriced.

sum of her cash position $M_h(t)$ and the current (dollar) value of the asset $D_h(t)p(t)$,

$$W_h(t) = D_h(t)p(t) + M_h(t). \tag{6.2}$$

When a fund manager borrows cash for leveraging positions, the cash $M_h(t)$ is negative, representing the fact that she has spent all her money and is in debt to the bank. Leverage λ_h is defined as the ratio between the fund manager's portfolio value and her wealth,

$$\lambda_h(t) = \frac{D_h(t)p(t)}{W_h(t)} = \frac{D_h(t)p(t)}{D_h(t)p(t) + M_h(t)}. \tag{6.3}$$

In case of short selling leverage is defined as the ratio of the asset side in the balance sheet and the wealth,

$$\lambda_h(t) = \frac{W_h(t) - D_h(t)p(t)}{W_h(t)} = \frac{M_h(t)}{D_h(t)p(t) + M_h(t)}. \tag{6.4}$$

The fund managers are value investors who base their demand $D_h(t)$ on a *mispricing signal*, $m(t) = V - p(t)$. For simplicity, the perceived fundamental value V is fixed at a constant value, which is the same for all fund managers and noise traders. Figure 6.2 shows demand $D_h(t)$ for a fund manager h

as a function of the perceived mispricing. As the mispricing increases, the fund manager wants a linear increase of the value of the portfolio, $D_h(t)p(t)$. However, this is bounded when it reaches the maximum leverage level $\lambda_{\max}$, set by the bank. Fund managers differ in their *aggression parameter* β_h, which quantifies how strongly they respond to the mispricing signal $m(t)$. When short selling is allowed[2], the fund manager's demand function, $D_h(t) = D_h(t, p(t))$, can be written as

$$D_h(t) = \begin{cases} (1-\lambda_{\max})W_h(t)/p(t) & \text{if } m(t) \leq m_{\text{crit}}^{\text{short}} \\ \lambda_{\max} W_h(t)/p(t) & \text{if } m(t) > m_{\text{crit}}^{\text{long}} \\ \beta_h m(t) W_h(t)/p(t) & \text{otherwise.} \end{cases} \tag{6.5}$$

The parameter $m_{\text{crit}} > 0$ is the critical value of the mispricing signal above which the fund manager is forced to flatten demand when short selling is not allowed, and similarly $m_{\text{crit}}^{\text{short}} < 0$ and $m_{\text{crit}}^{\text{long}} > 0$ are the corresponding parameters when short selling is allowed. Notice that $\lambda_{\max} > 1$ is strictly required for short-selling.

To summarize, consider the case where short selling is allowed. When the asset is strongly overpriced the value of the fund manager's position is constant at the value $D_h(t)p(t) = (1-\lambda_{\max})W_h(t)$. Similarly when the asset is strongly underpriced the value is constant at $\lambda_{\max} W_h(t)$. Anywhere in between the value is $\beta_h m(t) W_h(t)$, i.e. it is proportional to the aggression parameter β_h, the mispricing $m(t)$, the wealth $W_h(t)$.

Every fund manager is required by the bank to maintain $\lambda_h(t) \leq \lambda_{\max}$. If this condition would be violated the fund manager must adjust her demand to buy or sell assets to ensure that such a violation does not happen. This is known as meeting a *margin call*. The cause of a margin call can be either that the price drops from $p(t-1)$ to $p(t)$, causing $W_h(t)$ to fall by a larger percentage than the asset price (because of leverage), or that the wealth drops from $W_h(t-1)$ to $W_h(t)$ due to withdrawals (redemptions) from investors, as will be discussed below. Fund managers adjust their positions within each time step to make sure that this condition is never violated.

The *noise trader* demand is formulated in terms of the value $\xi_{\text{n}}(t) = D_{\text{n}}(t)p(t)$, whose logarithm follows an Ornstein–Uhlenbeck random process of the form

$$\log \xi_{\text{n}}(t) = \rho \log \xi_{\text{n}}(t-1) + \sigma_{\text{n}} \chi(t) + (1-\rho)\log(VN), \tag{6.6}$$

where χ is independent and normally distributed with mean zero and standard deviation one, and where $0 < \rho < 1$. The Ornstein-Uhlenbeck process is a

[2] If short selling is not allowed $m_{\text{crit}}^{\text{short}} = 0$ and in the first line $D_h(t) = 0$. See Kerbl [168]: p. 6 for fund manager's demand when short selling is allowed.

widely used approach to model currency exchange rates, interest rates, and commodity prices stochastically. In the limit as $\rho \to 1$, i.e. without the mean reversion, the log-returns $r(t) = \log p(t+1) - \log p(t)$ of the asset price are normally distributed. We choose a value of ρ close to one so that without fund managers the price is weakly mean reverting around the fundamental value V and the log-returns are nearly normally distributed.

6.2.2 Dealing with defaults and their propagation

If the fund manager's wealth ever becomes negative, i.e. if $W_h(t) < 0$, the fund manager defaults and goes out of business. The fund manager must then sell all assets ($D_h(t) = 0$) and use the revenue to pay off as much of the loan as possible. All remaining loss is born by the bank, causing capital shortfall, which has to be provided by the government or a bailout fund. For simplicity, we assume banks always receive the necessary bailout funds and they continue to lend to other fund managers as before. $T_{\mathrm{re-intro}}$ timesteps later the defaulting fund manager re-emerges as a new fund manager, as described below.

6.2.3 Wealth distributions of the agents

Initially each fund manager has the same endowment, $W_h(0) = W_0$. The wealth of the fund manager then evolves according to

$$W_h(t) = W_h(t-1) + D_h(t-1)[p(t) - p(t-1)] + F_h(t), \tag{6.7}$$

where $D_h(t-1)[p(t) - p(t-1)]$ reflects the profits and losses from trading of the fund manager's portfolio and $F_h(t)$ quantifies the deposits or withdrawals of the fund investor.

The fund investor deposits or withdraws from each fund manager based on an exponential moving average of the recent performance with smoothing parameter a. This is measured by the rate of return in comparison to a benchmark return r_b. This prevents the wealth of the fund managers from growing indefinitely, and makes possible well defined statistical averages for properties such as returns and volatility. Let

$$r_h(t) = \frac{D_h(t-1)[p(t) - p(t-1)]}{W_h(t-1)}, \tag{6.8}$$

be the rate of return of fund manager h. The fund investors base their decisions on the recent performance of fund h, measured as an exponential moving average of the rate of return

$$r_h^{\mathrm{perf}}(t) = (1 - a)\, r_h^{\mathrm{perf}}(t - 1) + a\, r_h(t). \tag{6.9}$$

The amount of cash a fund manager would have if selling all assets at the current price is

$$\tilde{M}_h(t) = D(t - 1)p(t) + M(t - 1). \tag{6.10}$$

The flow of capital in or out of fund h is given by

$$F_h(t) = \max\left[-1, b\left(r_h^{\mathrm{perf}}(t) - r_b\right)\right] \max\left[0, \tilde{M}_h(t)\right], \tag{6.11}$$

where b is a parameter controlling the fraction of capital withdrawn or invested, a is the moving average parameter, and r_b is the benchmark return of the investors. This process is well documented, see e.g. Busse [170], Chevalier and Ellison [171], Del Guercio and Tka [172], Remolona et al. [173], Sirri and Tufano [174]. Fund investors cannot take out more cash than the fund manager has.

In case a fund manager's wealth falls below a critical threshold, W_{crit}, the fund manager goes out of business. This avoids the possibility of "zombie funds", which persist for many time steps with nearly no wealth and no relevance for the market. After $T_{\mathrm{re-intro}}$ time steps, funds that default are replaced with a new fund with initial wealth W_0 and the same aggression parameter β_h.

6.3 Implementation of regulatory measures

We now introduce two regulatory policies. The first is the regulatory measure to reduce credit risk encouraged by the Basle II framework. The second regulation policy is an alternative proposal in which all risk associated with leverage is required to be perfectly hedged by options.

6.3.1 Modeling the state of the art: Basle II

The Basle II scheme that we employ here models the risk control policies used by banks regulated under the Basle II framework. These banks use internal models to determine the value of their risk-weighted assets. The banks are allowed discretion in their risk control as long as it is Basle II compliant. We implement a Basel compliant model that is used in practice by banks.

6.3.1.1 What is credit risk?

According to the Basle II capital adequacy rules banks have to allocate capital for their credit exposure. The capital can be reduced through credit mitigation techniques, such as taking collateral (e.g. securities or cash) from the counterparty on the loan. This reduces their net adjusted exposure. However, to provide a safety margin haircuts are also applied to both the exposure and the collateral. *Haircuts* are percentages that are either added or subtracted depending on the context in order to provide a safety buffer. In the case of a collateralized loan, in the absence of haircuts, the net exposure taking the risk mitigating effect of the collateral into account is $E^* = E - k$, where k is the value of the collateral. However, when haircuts are applied the value of the raw exposure E is adjusted upward to $E(1 + H_e)$, where $H_e \geq 0$ is the haircut on the exposure, and the value of the collateral k is adjusted downward to $k(1 - H_{col})$, where $H_{col} \geq 0$ is the haircut on the collateral. Thus the net exposure taking the risk mitigating effect of the collateral into account is[3]

$$E^* = \max[0, E(1 + H_e) - k(1 - H_{\mathrm{col}})], \tag{6.12}$$

The “max” is present to make sure the exposure is never negative.

6.3.1.2 Implementation of “Haircuts”

The basic idea is that undervaluing the asset creates a safety buffer which decreases the likelihood that at some point in the future the value of the collateral will be insufficient to cover possible losses. Increasing collateral has the dual effect of decreasing the chance that the collateral might be insufficient to cover future losses, and of decreasing the size of loans when collateral is in short supply. In general, the size of the haircut, and hence the size of the exposure and collateral, depends on volatility.

Haircuts can either be standard supervisory haircuts, issued by regulatory bodies[4], or internal estimates of banks. Permission to use internal estimates is conditional on meeting a set of minimum standards[5]. Here we use a simple approach – used in practice by banks for their own internal estimates satisfying the Basle II standards – and compute the haircuts H_{col} using a

[3] See Bank for International Settlements [62]: §147.

[4] See Bank for International Settlements [62]: §147 for recommendation on supervisory haircuts, e.g. haircut for equities listed on a recognized exchange is 25%.

[5] See Bank for International Settlements [62]: §156-165 for qualitative and quantitative standards.

formula that sets a minimum floor on the haircut $H_{\min}$ with an additional term that increases with the historical volatility $\sigma(t)$, measured in terms of standard deviation of log-returns over τ time steps. We assume a loan of time duration T and a fixed cost c. The haircut is given by the formula

$$H_{\mathrm{col}}(t) = \min\left[\max\left(H_{\min}, \Phi\sigma(t)\sqrt{T} + c\right), 1\right], \tag{6.13}$$

where Φ is a confidence interval set by the bank in accordance with the regulatory body[6]. The use of the "min" and "max" guarantees that the haircut is always in the range $H_{\min} \leq H_{\mathrm{col}} \leq 1$.

The choice of a haircut implies a variable maximum leverage $\lambda_{\max}^{\mathrm{adapt}}(t)$. Suppose a bank makes a loan of size L to a fund that pledges the shares of the asset it buys as collateral. Then the raw exposure is $E = L$ and the value of the shares of the asset is k. By definition the leverage is

$$\lambda_{\max}^{\mathrm{adapt}}(t) = \frac{k}{k - E}. \tag{6.14}$$

Since the exposure is cash no haircut is required and $H_e = 0$, but the collateral is risky, so $H_{\mathrm{col}} > 0$. If the net risk mitigated exposure $E^* = 0$, then combining eq. (6.12) and eq. (6.14) implies

$$\lambda_{\max}^{\mathrm{adapt}}(t) = \frac{1}{H_{\mathrm{col}}(t)}. \tag{6.15}$$

For short selling the fund borrows the asset (which is risky) and gives cash as collateral, so the situation is reversed, and $H_{\mathrm{col}} = 0$ with $H_e > 0$. In this case H_e is set according to eq. (6.13) with H_e on the lefthand side instead of H_{col}, and through similar logic $\lambda_{\max}^{\mathrm{adapt}}(t) = 1/H_e(t)$. This shows explicitly how the haircuts impose a limit on the maximum leverage. For example, if the haircut is 0.5 the maximum leverage is 2, whereas if the haircut is 0.1 the maximum leverage is 10.

To make correspondence with the unregulated case we set $H_{\min} = 1/\lambda_{\max}$ and $\Phi = 1/\lambda_{\max}\sigma_b$, where σ_b is a benchmark volatility that serves as an exogenous parameter. Furthermore, for simplicity we set transaction costs to zero, i.e. $c = 0$, and the holding duration of the collateral to one time step, $T = 1$. Then by combining eq. (6.13) and eq. (6.15) we see that the adaptive maximum leverage explicitly depends on volatility,

$$\lambda_{\max}^{\mathrm{adapt}}(t) = \max\left[\lambda_{\max}\min\left(1, \frac{\sigma_b}{\sigma(t)}\right), 1\right]. \tag{6.16}$$

[6] According to the Basel framework Φ must be chosen such that given a historical volatility $\sigma(t)$ the haircut is sufficient in 99% of cases. See [62]: §156.

If the historical volatility $\sigma(t) \leq \sigma_b$ then full maximum leverage $\lambda_{\max}$ can be used by the fund managers. When the simulation is operating under the Basle II scheme the $\lambda_{\max}$ in the fund manager's demand of eq. (6.5) is replaced by $\lambda_{\max}^{\text{adapt}}(t)$ in eq. (6.16).

6.3.1.3 Implementation of credit spreads

To determine interest rates on loans to fund managers, banks add a risk premium (spread) S to a benchmark interest rate i_b. Usually S is determined by rating a customer, but in many cases such as margin trading a fixed risk premium is used for all customers of a given type. We use a fixed spread S for all fund managers. The interest rate for the fund manager h is

$$i_h = i_b + S. \tag{6.17}$$

To implement borrowing costs in the agent-based model we set the benchmark interest rate $i_b = 0$ and add a term accounting for the spread S to eq. (6.7). Fund managers always pay the borrowing costs for the previous time step. In case the fund manager takes a leveraged long position (M_h is negative) her wealth is

$$W_h(t) = W_h(t-1) + D_h(t-1)[p(t) - p(t-1)] + F_h(t) + M_h(t-1)S, \tag{6.18}$$

and in case of short selling, where the demand is negative,

$$W_h(t) = W_h(t-1) + D_h(t-1)[p(t) - p(t-1)] + F_h(t) + D_h(t-1)p(t-1)S. \tag{6.19}$$

The maximum amount the fund investor can redeem from the fund manager has to be adjusted from eq. (6.10) to

$$\begin{aligned} \tilde{M}_h(t) &= D(t-1)p(t) + M(t-1)[1+S] && [\text{long}] \\ \tilde{M}_h(t) &= D(t-1)p(t) + M(t-1) + D_h(t-1)p(t-1)S && [\text{short}]. \end{aligned} \tag{6.20}$$

Obligations to banks are satisfied *before* those of investors, as is the usual practice.

6.3.2 The ideal world: the perfect-hedge scheme

The idea behind the perfect-hedge scheme is that, in addition to holding the shares of the asset as collateral, banks require all loans to be hedged by options. Thus barring default of the issuer of the option, the loan is completely secure.

6.3.2.1 How to hedge against credit risk?

We first consider the case where the fund is long, in which case the bank requires it to buy a put with strike price K_{put}. For simplicity we treat the loan as an overnight loan and thus the put has a maturity of one day. To make sure that the loan can be repaid, the value of the asset must equal the value of the loan. If the price of the asset when the loan is made is $p(t)$, from eq. (6.14) the fraction by which it can drop in price before the value of the collateral is less than that of the original loan is $(k - E)/E = 1/\lambda_h(t)$. The strike price is thus

$$K_{\text{put}}(t) = p(t)\left(1 - \frac{1}{\lambda_h(t)}\right), \tag{6.21}$$

and via similar reasoning, in the case where the fund is short it buys a call option with strike price

$$K_{\text{call}}(t) = p(t)\left(1 + \frac{1}{\lambda_h(t) - 1}\right). \tag{6.22}$$

Option prices are assumed to obey the Black-Scholes formula [175]. The option price is calculated based the following parameters: The spot price of the underlying asset is $p(t)$, the risk-free interest rate $r = 0$, and the volatility $\sigma = \theta\sigma(t)$, where $\sigma(t)$ is the historical volatility[7]. When the fund is long the strike price P_h of the put option is $K = K_{\text{put}}$ and when it is short the strike price C_h of the call option is K_{call}. Note that the option prices depend on the leverage through the strike prices; as the leverage increases the options get closer to be in the money and so their price increases.

To implement the hedging costs in the model we add a term for the option costs to eq. (6.7). In case the fund manager holds a long position whose hedging cost is $P_h(t)D_h(t-1)$ and the wealth becomes

$$W_h(t) = W_h(t-1) + D_h(t-1)[p(t) - p(t-1)] + F_h(t) - D_h(t-1)P_h(t-1), \tag{6.23}$$

and similarly for short selling

$$W_h(t) = W_h(t-1) + D_h(t-1)[p(t) - p(t-1)] + F_h(t) + D_h(t-1)C_h(t-1). \tag{6.24}$$

The maximum redemption of fund investors is adjusted for long positions

$$\tilde{M}_h(t) = D(t-1)p(t) + M(t-1)) - D_h(t-1)P_h(t-1), \tag{6.25}$$

[7] We use the historical volatility $\sigma(t)$, defined as the standard deviation of the log-returns of the underlying asset over τ time steps. Volatility is multiplied by an arbitrary factor θ to gauge the length of one time step. In the simulations we set $\theta = 5$.

and for short selling is

$$\tilde{M_h}(t) = D(t-1)p(t) + M(t-1)) + D_h(t-1)C_h(t-1). \qquad (6.26)$$

Note that under this scheme the only risk for the bank is that in case the fund defaults, it will not be able to pay for the hedging costs $P_h(t-1)$ at the previous time step.

To make a correspondence to the spreads defined under the Basle II agreement, the *effective spreads* are[8]

$$S_h^{[\text{long}]}(t) = \frac{P_h(t)}{p(t)\left(1 - \frac{1}{\lambda_h(t)}\right)} \qquad \text{and} \qquad S_h^{[\text{short}]}(t) = \frac{C_h(t)}{p(t)}. \qquad (6.28)$$

6.3.2.2 Limit on hedging costs and maximum leverage

Absent any other constraints, under the above scheme there is the possibility that the maximum leverage could become arbitrarily large, and consequently the hedging costs could become very high. We prevent this by limiting leverage. To compute the limit on leverage needed to keep the hedging cost below a given threshold, for long positions we impose a maximum hedging cost P_{max}. The corresponding dynamic maximum leverage $\lambda_{\text{max}}^{\text{hedge}}(t)$ can then be found by solving

$$P(p(t), \sigma(t), \lambda_{\text{max}}^{\text{hedge}}(t)) = P_{\text{max}}(t), \qquad (6.29)$$

for $\lambda_{\text{max}}^{\text{hedge}}(t)$. Similarly, just as in the Basle II scheme, there is the possibility that historical volatility (eq. (6.28)) could become arbitrarily low. To prevent this we solve the same equation assuming a fixed volatility floor σ_b, which gives the maximum leverage as the solution of

$$P(p(t), \sigma_b, \lambda_{\text{max}}) = P_{\text{max}}(t), \qquad (6.30)$$

[8] To see this, note that $D_h(t)P_h(t)$ or $D_h(t)C_h(t)$ is the effective interest the funds have to pay for being long or short, respectively. To calculate an *interest rate* we divide the interest by the loan size, i.e.

$$\frac{D_h(t)P_h(t)}{D_h(t)p(t) - W_h(t)} = \frac{D_h(t)P_h(t)}{-M_h(t)}. \qquad (6.27)$$

Note that $M_h(t)$ is negative because the fund *owes* cash to the bank. By substituting $W_h(t) = D_h(t)p(t)/\lambda_h(t)$ in Eq. (16) we obtain eq. (6.28). In case of short selling the interest rate divided by the loan size is $(D_h(t)C_h(t))/(D_h(t)p(t)) = C_h(t)/p_h(t)$.

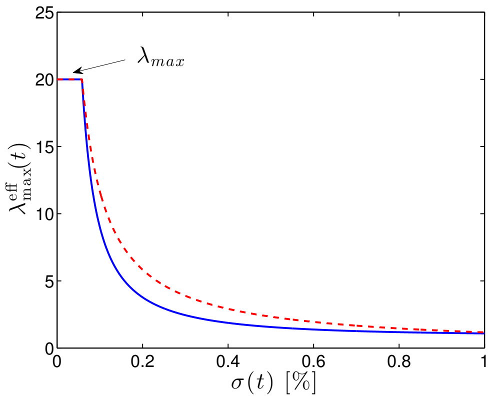


Figure 6.3: Maximum leverage function $\lambda^{\mathrm{adapt}}_{\mathrm{max}}(t)$ for fund managers as a function of historical volatility $\sigma(t)$ for the two regulation schemes. The dashed red curve shows the Basle II scheme of eq. (6.16), the solid blue curve shows the perfect-hedge scheme of eq. (6.31).

for λ_{max}. Finally, the leverage maximum $\lambda^{\mathrm{adapt}}_{\mathrm{max}}(t)$ is their minimum, i.e.

$$\lambda^{\mathrm{adapt}}_{\mathrm{max}}(t) = \min\left[\lambda_{\mathrm{max}}, \lambda^{\mathrm{hedge}}_{\mathrm{max}}(t)\right] . \tag{6.31}$$

The perfect-hedge version of the agent-based model is obtained by replacing the maximum leverage of eq. (6.5) by eq. (6.31). Analogous equations hold for the short selling scenario. See fig. 6.3 for the dependence of $\lambda^{\mathrm{adapt}}_{\mathrm{max}}(t)$ as a function of $\sigma(t)$.

6.4 Impact of regulatory measures on systemic risk

6.4.1 Financial performance and efficiency indicators of the agents

As performance indicators we use return to fund investors, profits to the fund managers, and probability of default. Since the fund investor actively invests and withdraws money from fund managers and funds have to cover for expenses, i.e. interest payments, the rate of return $r_h(t)$ does not properly capture the actual return to fund investors. To solve this accounting problem we compute the adjusted rate of return r^{adj} to fund investors for any given period from $t = 0$ to $t = T$. This is done by adjusting the wealth $W_h(t)$ of fund managers by the net flow of capital and the expenses within a given period, according to

$$r_h^{adj}(T) = \frac{W_h^{adj}(T)}{W_h(0)} - 1 \tag{6.32}$$

with

$$W_h^{adj}(T) = W_h(T) - \sum_{i=0}^{T} F_h(i) + f(T), \tag{6.33}$$

where f is an adjustment for the expenses of the fund manager in a given period. In particular we have for long position under the Basle II scheme

$$f(T) = \sum_{i=0}^{T} M_h(i)S, \tag{6.34}$$

and in the perfect hedge case

$$f(T) = \sum_{i=0}^{T} D_h(i)P_h(i). \tag{6.35}$$

Expenses of fund managers for short positions are calculated in a similar way as described in section 6.3.1.3 and section 6.3.2.2. If a fund manager is out of business at $t = T$, $W_h(T)$ is set to zero and $r_h^{adj}(T)$ will be close to -1, deviations coming from the net flow of capital and expenses of the fund manager in the given period.

For management fees we use a hypothetical 2% fixed fee for assets under management and a 20% performance fee, paid by the fund investor to the fund managers. These fees are hypothetical and are not used as actual transactions in the model. They are only to indicate the profitability of fund managers under various conditions. If a fund manager goes out of business management fees are not paid.

We also consider the average annualized cost of capital, which is the effective interest rate $i_h(t)$ from eq. (6.17) and eq. (6.28). By annualized we mean that one simulation time step represents five trading days and one year has 250 trading days. As performance indicators we monitor the standard deviation of the log-returns $r(t)$ for all time steps from an entire simulation run as an asset volatility "index". Additionally we calculated the distortion as defined in [167], i.e. the average absolute distance between log price and log fundamental V. Note that in our case the distortion is closely related to volatility. We explicitly checked that the distortion closely follows the curves of fig. 6.7(a). As a measure for trading volume we use the average number of shares traded per time step, $1/HT \sum_{h=1}^{H} \sum_{t=1}^{T} |D_h(t) - D_h(t-1)|$, with T denoting the number of time steps in a simulation run and the number of fund managers $H = 10$. Finally, we measure the capital shortfall of banks by just keeping track of the amount of money they lose when funds default.

6.4.2 The parameters of the model: model calibration

For all simulations we used 10 fund managers with $\beta_h = 5, 10, \ldots, 50$, and simulation parameters $\rho = 0.99$, $\sigma_\mathrm{n} = 0.035$, $V = 1$, $N = 1 \times 10^9$, $r_b = 0.003$, $a = 0.1$, $b = 0.15$, $W_0 = 2 \times 10^6$, $W_\mathrm{crit} = 2 \times 10^5$, $T_\mathrm{re-intro} = 100$, $\tau = 10$, $\theta = 5$, $\sigma_b = 0.01175$ and $S = 0.00015$. For most runs we used a range of $\lambda_\mathrm{max} \in [1, ..., 20]$.

To test the robustness of the model we tested several different parameter sets, varied key parameters and motivated parameter choices in their economic context. A complete analysis of the robustness of the model is not feasible because of the large number of parameters, and because several parameters cannot be set independently.

Reducing or increasing the number of fund managers H affects the wealth $W_h(t)$ of individual fund managers. With more fund managers individual banks accumulate less wealth. Therefore individual bankruptcies of fund managers become less severe resulting in lower capital shortfall for banks. Increasing the aggressiveness of fund managers β_h causes them to react more to mispricing, resulting in more margin calls and subsequent defaults.

The parameters ρ, σ_n, V, N determine the demand of noise traders. σ_n is set to reflect typical stock price fluctuations. N, V and W_0 are chosen to guarantee that fund managers have a low market share when they are introduced in market. We choose to arbitrarily set $V = 1$ and choose N and W_0 accordingly. The setting of $\rho \sim 1$ ensures that the deviation from the normal distribution is minimal. With $\rho = 0.99$ the typical fluctuation in volatility is about 1%, which is a reasonable volume given real stock values.

The benchmark return r^b plays the important role of determining the relative size of hedge funds vs. noise traders. If the benchmark return is set very low then funds will become very wealthy and will buy a large quantity of the asset under even small mispricings, preventing the mispricing from ever growing large. This effectively induces a hard floor on prices. If the benchmark return is set very high, funds accumulate little wealth and play a negligible role in price formation. The interesting behavior is observed at intermediate values of r^b where the funds' demand is comparable to that of the noise traders. The parameter "a" governs the exponential moving average of the performance of fund managers and the parameter "b" controls the sensitivity of withdrawals or contributions of fund investors. Both parameters a and b are set empirically, following work from [170],[171], [172], [173] and [174].

Using a positive survival threshold for removing funds W_{crit} avoids the creation of "zombie funds" that persist for long periods of time with almost no wealth. Setting $T_{\mathrm{re-intro}} = 100$, which controls the reintroduction of funds after bankruptcies, corresponds to 2 years under the calibration that one time step is five days, which we think is a reasonable value. Higher settings for $T_{\mathrm{re-intro}}$ result in simulations with few fund managers present at turbulent times.

The parameter τ is chosen to measure historical volatility over a short window. Choosing different windows τ $5 < \tau < 20$ does not substantially influence the simulations.

The parameter θ is an arbitrary factor that sets the length of one time step. We choose to use a calibration in which one time step is five days and a year has 250 trading days. This calibration seems reasonable considering several factors such as the average rate of return to fund investors, which would be $\sim 8\%$ (for high leverage scenarios, not considering defaults) or the benchmark rate of return, which would be 15%.

The benchmark volatility σ_b is set empirically to a very low volatility that is only reached in tranquil times. Alternatively, it would be possible to refrain from using σ_b and set $H_{\min}$ and Φ or $P_{\max}$ directly.

The parameter S is a risk premium (spread) to a benchmark interest rate i_b, see above. We use a fixed spread S for all fund managers of 0.75%. This low risk premium of approximately 1% reflects the fact that loans are fully collateralized in the model.

6.4.3 Origin of fat tails in the distribution of returns

The statistical properties of asset price returns change considerably with increasing leverage. Figure 6.4 shows the distribution of log-returns $r(t)$ for four cases: (i) For the case of noise traders only, log-returns are almost normally distributed. (ii) With un-leveraged fund managers, volatility is slightly reduced but log-returns remain nearly normally distributed. (iii) When leverage is increased to $\lambda_{\max} = 15$ and no short selling is allowed, the distribution becomes thinner for small $r(t)$ but the negative returns develop fat tails. The asymmetry arises because with a short selling ban in place

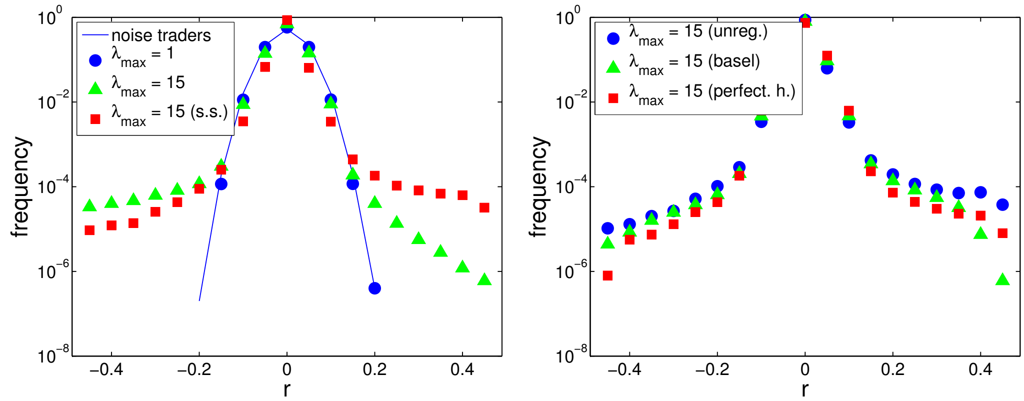


Figure 6.4: The distribution of log-returns r. (a) Return distributions of the baseline model (with parameters from section 6.4.2) in semi-log scale. The un-leveraged case (blue circles) practically matches the case with only noise traders (blue curve). When the maximum leverage is raised to $\lambda_{\max} = 15$ (red squares) the distribution becomes more leptokurtic, and negative returns develop a fat tail. With short selling (demand eq. (6.5)) the distribution becomes even thinner and tails turn fat on both sides. (b) Return distributions for the three regulation schemes at $\lambda_{\max} = 15$.

fund managers are only active when the asset is underpriced, i.e. when the mispricing $m(t) > 0$. Finally, when short selling is allowed (iv), the distribution becomes yet more concentrated in the center and fat tails develop on both sides. Due to higher risk involving short selling, the distribution becomes slightly asymmetric. This higher short selling risk arises because of the different risk profile of long and short positions. The potential losses from long positions are limited, since the price cannot go below zero. This is not the case for short positions, where the loss potential has no limit. Note that in all cases the autocorrelation of signed returns is very small, whereas the autocorrelation of absolute returns is strongly positive and decays slowly.

6.4.4 Time series analysis and the volatility profile

The time series shown in fig. 6.5 are computed for the perfect-hedge scheme when short selling is allowed at $\lambda_{\max} = 15$. Figure 6.5(a) shows the wealth $W_h(t)$ for all 10 fund managers over time. Figure 6.5(b) shows the historical asset volatility and fig. 6.5(c) shows the time series of the asset price $p(t)$. The leverage cycle can be observed in this figure. Initially, all fund managers

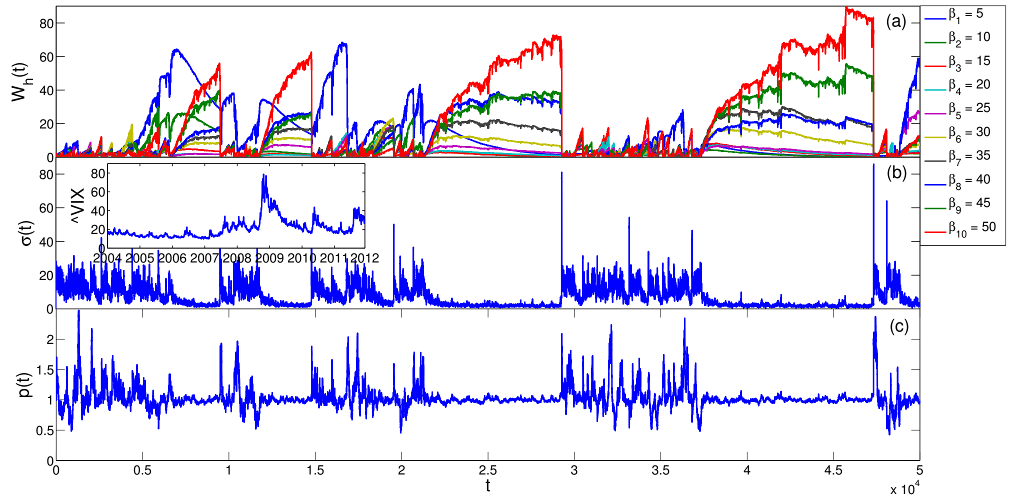


Figure 6.5: Time series for perfect-hedge scheme for 10 fund managers with $\beta_h = 5, 10, \ldots, 50$, for $\lambda_{\max} = 15$. The simulation was done for the perfect-hedge scheme with maximum leverage eq. (6.31) and wealth eq. (6.23) and eq. (6.24). Simulation parameters are listed in section 6.4.2. (a) Wealth time series $W_h(t)$ of the fund managers. (b) Historical volatilities over a $\tau = 10$ time step window. For reference, in a market with noise traders only, the volatility is about $\sigma(t) \approx 17.5$ percent. For comparison the inset shows the VIX (Chicago Board Options Exchange Market Volatility Index), a measure of the implied volatility of S&P 500 index options from 2004 to 2012. Our model reproduces the asymmetric profile in which volatility bursts are initiated by a rapid rise followed by a gradual fall. (c) Time series of the asset price $p(t)$.

start with $W_h(0) = 2$ and have a marginal influence on the market. As they gain more wealth their market impact increases, mispricings are damped and the asset volatility decreases. The decrease in volatility results in lower borrowing cost for the fund managers. Lower borrowing costs allow them to use a higher leverage, which further lowers volatility, resulting in even lower borrowing costs etc.. This leads to seemingly stable market conditions with low volatility and low borrowing costs for fund managers; such stable periods can persist for a long time. Occasionally the stable periods are interrupted by crashes. These are triggered by small fluctuations of the noise trader demand. As shown in [31], if one or more of the funds is at its leverage limit, a downward fluctuation in price causes the leverage to rise. This triggers a margin call, which forces the fund to sell into a falling market, amplifying the downward fluctuation. This may cause other funds to sell, driving prices even further down, to cause a crash. Such crashes can trigger price drops as large as 50%, which cause the more highly leveraged fund managers to default. After a crash noise traders dominate and volatility is high. Fund managers are reintroduced; as their wealth grows volatility drops, and the leverage cycle starts again. In situations where a crash wipes out all but the least aggressive fund managers, as happens around $t = 29,000$ and at about $t = 47,000$, the surviving less aggressive fund managers become dominant for extended periods of time.

One of the interesting aspects of our model is that it reproduces the asymmetric profile of volatility bursts. The inset of fig. 6.5(b) shows the VIX (Chicago Board Options Exchange Market Volatility Index), which is a measure of the implied volatility of S&P 500 index options, from 2004 to 2012. As can be seen by eye in this figure, in our model, as in the real data, volatility bursts rise rapidly and damps out gradually, forming a very characteristic asymmetric peak.

To see this more quantitatively in fig. 6.6 we compare the peak behaviors of the VIX, our model and a GARCH(1,1) model. Two example time series around a peak are shown for each. The data is normalized so that the peaks are all of the same height. The time axis is shifted so that peaks occur at $t = 500$. Otherwise, the time axis is not normalized or gauged to real time. We fit the rise and decay around the peaks as a power law of the form $\sigma(t) \underset{\sim}{\propto} t^k$, characterizing the rise by $k = k_1$ and the decay by $k = k_2$, and take the average for the largest peaks in the time series, both from the VIX and from our model. To determine which peaks to fit, we selected local maxima that are at least $(\max(\mathrm{VIX}) - \min(\mathrm{VIX}))/4$) or $(\max(\sigma(t)) - \min(\sigma(t)))/4)$ above the surrounding data. The fitted values for the rise of the VIX are $k_1 \sim 16.39$ and for our model $k_1 \sim 9.19$. The VIX gradually falls with $k_2 \sim -2.34$ and

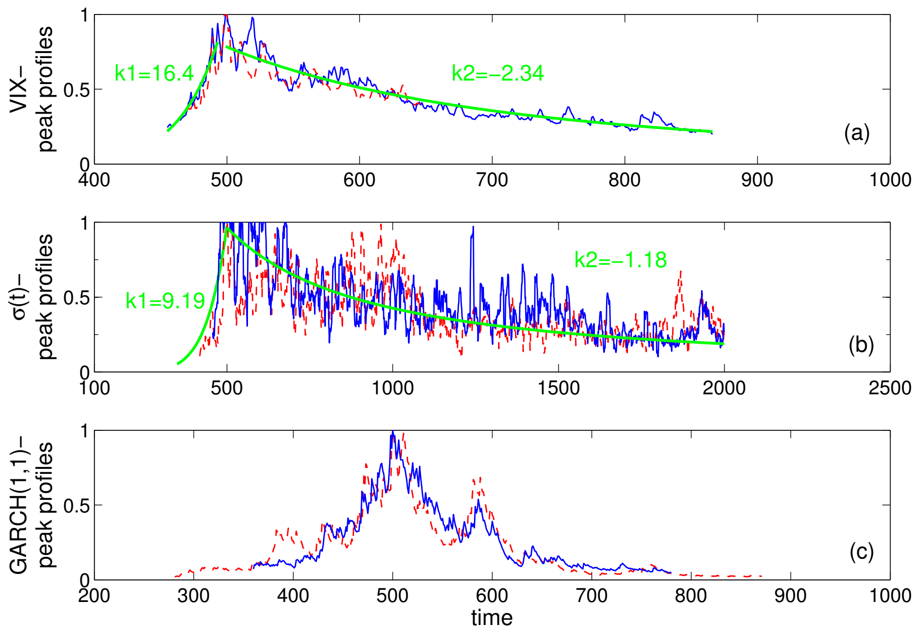


Figure 6.6: Peak behavior of the VIX (a), our model (b) and a GARCH(1,1) model (c). We find that the rise and fall of volatility during a peak follows roughly a power law of the form $\sigma(t) \propto\!\!\!\!\sim t^k$. The fitted values for the rise of the VIX are $k_1 \sim 16.39$ and for our model $k_1 \sim 9.19$. The VIX gradually falls with $k_2 \sim -2.34$ and for our model with $k_2 \sim -1.18$. GARCH models do not exhibit power-law behavior, and k_1 and k_2 can not be fitted. In each case we show two characteristic time series in blue (solid line) and red (dashed line), normalized to have the same peak height. The time axis is shifted so that peaks occur at $t = 500$. Otherwise, the time axis is not normalized or gauged to real time.

for our model with $k_2 \sim -1.18$. GARCH models do not exhibit power-law behavior and k_1 and k_2 cannot be fitted. Note that while the form of the peaks is the same for the VIX and our model, the magnitude is not; also the VIX follows the profile with less noise than our model does. A possible reason for this is that the VIX shows the implied volatility of S&P 500 index, while our model shows the volatility of a single asset.

As a further statistical comparison we calculated the standardized moments skewness and kurtosis. The skewness of the VIX (~ 2.02) is virtually identical to our model (~ 2.01), however the kurtosis of the VIX (~ 8.13) is lower compared to our model (~ 14.59). Note that the VIX shows even in tranquil times quite substantial volatility in comparison to our model, where extended periods with almost no volatility can be observed. The reason for this is that in times of high market share of the fund managers, the effect on the asset price of the noise traders is negligible. All fund managers have the same perceived fundamental value V and thus stabilize the asset price to a point where almost no volatility can be observed. With a different fundamental value V_h for every fund manager the behavior would become less synchronized and therefore, even in tranquil times, volatility would remain at a substantial level. We have explicitly checked this in a series of experiments.

6.4.5 Comparison of the different regulatory schemes

In the following we illustrate the impacts of the three regulatory schemes:

1. The unregulated baseline scheme from section 6.2 with fixed maximum leverage $\lambda_{\max}$, corresponding to demand eq. (6.5).
2. The Basle II scheme, which has the same demand equation but with $\lambda_{\max}$ replaced by $\lambda_{\max}^{\text{adapt}}(t)$ of eq. (6.16) and the wealth update given by eq. (6.18) and eq. (6.19).
3. The perfect-hedge scheme, where $\lambda_{\max}^{\text{adapt}}(t)$ is given by eq. (6.31) and the wealth update is eq. (6.23) and eq. (6.24).

For all simulations we used the parameters listed in section 6.4.2 and enabled short selling. λ_{max} was varied from 1 to 20. For each parameter set we compute 5×10^4 time steps and average over 100 independent runs. The following indicators are annualized using a calibration in which one time step is five days and a year has 250 trading days. This calibration seems reasonable considering several factors such as the average rate of return to fund investors,

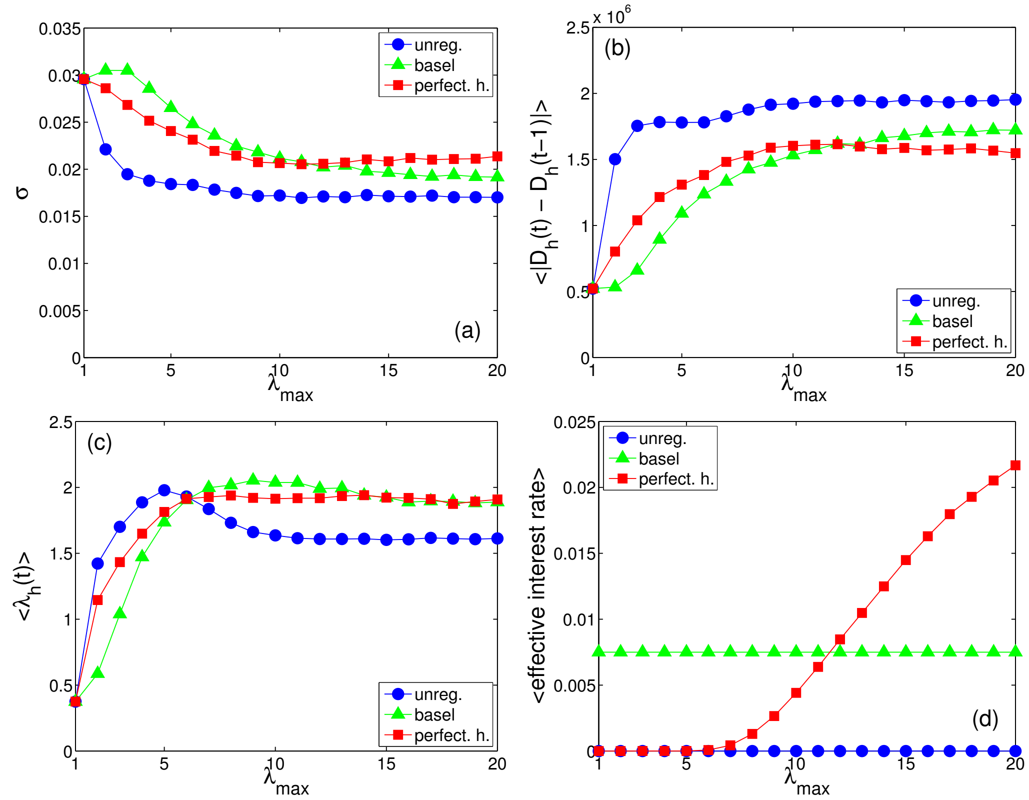


Figure 6.7: Impacts of regulatory measures on market indicators as $\lambda_{\max}$ varies. (a) Volatility of the underlying asset. (b) Market volume of the underlying asset, measured by the average amount of shares traded by a fund manager per time step. (c) Average effective leverage of fund managers. (d) Average annualized effective interest rate. For all simulations we used 10 fund managers with $\beta_h = 5, 10, \ldots, 50$ over 5×10^4 time steps. Simulation parameters listed in section 6.4.2, short selling was allowed. For all indicators it is assumed that one time step takes five days and a year has 250 trading days. Blue, green, and red curves indicate the unregulated, the Basle II, and the perfect-hedge scheme, respectively. Standard deviations computed over 100 independent runs are below symbol size.

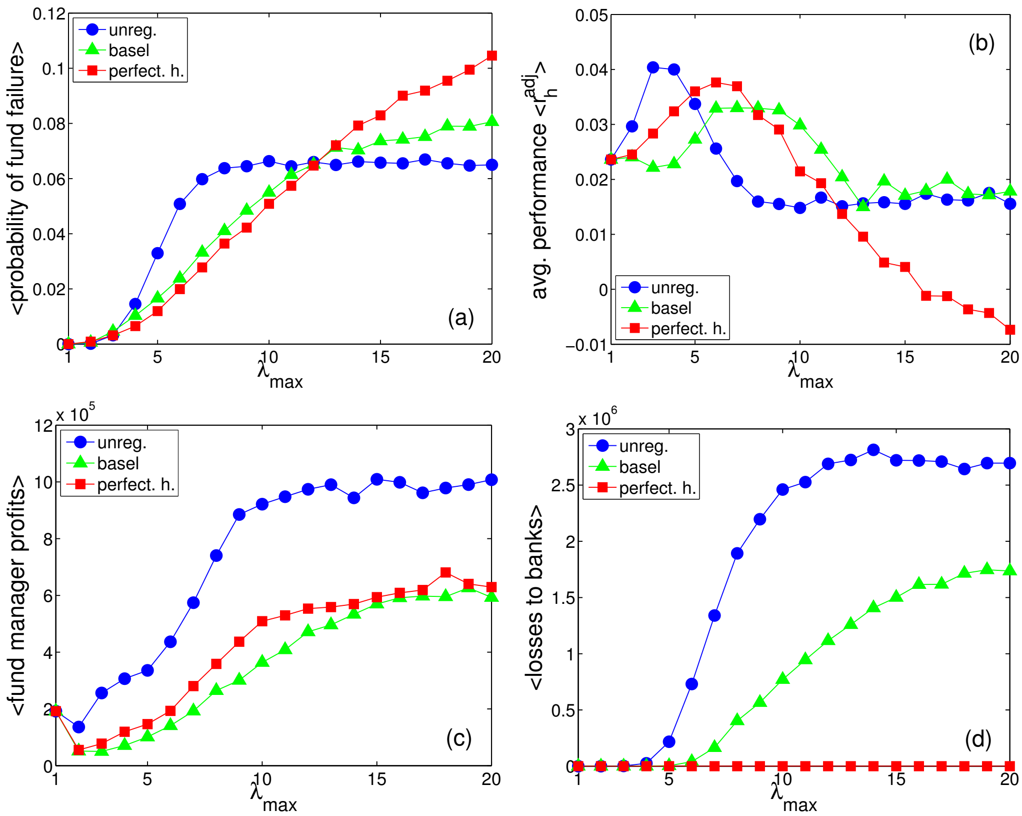


Figure 6.8: Impacts of regulatory measures on performance indicators for the most aggressive fund manager with $\beta_h = 50$ as $\lambda_{\max}$ varies. (a) Average annual probability of fund failure. (b) Average annual adjusted rate of return r^{adj} to fund investors. (c) Average annual profits to the fund managers. (d) Annual capital shortfall of banks. For all simulations we used the same setup as in the previous figure. Standard deviations computed over 100 independent runs are about 0.01, 0.01, 2.7×10^5 and 5.4×10^5 for (a), (b), (c) and (d), respectively.

which would be $\sim 8\%$ (for high leverage scenarios, not considering defaults) or the benchmark rate of return, which would be 15%.

Figure 6.7 provides a panel of results that show how market characteristics such as (a) price volatility, (b) trading volume, (c) average leverage and (d) the effective interest rate are affected by varying of the maximum leverage parameter $\lambda_{\max}$ under each of the three regulatory schemes. For the unregulated case the volatility drops monotonically as $\lambda_{\max}$ increases, dropping by almost a factor of two for $1 < \lambda_{\max} < 10$ and then reaching a plateau. The reason the volatility drops is that the presence of value investors ordinarily damps volatility, since they buy when prices fall and sell when prices rise. Larger leverage means more trading and it also means higher profits for a given level of trading, which means investors place more money in the funds and they have more market power. The resulting increase in trading is evident in fig. 6.7(b): Between $\lambda_{\max} = 1$ and $\lambda_{\max} = 3$ the trading volume increases by more than a factor of three, and then more or less levels off.

Volatility is not significantly influenced by failures of fund managers. Bankruptcies of the most aggressive fund manager occur on average every 800 time steps for $\lambda_{\max} > 7$. Therefore, the subsequent price drops or jumps do not occur frequently enough to substantially influence volatility.

The behavior of the volatility under the Basle II scheme is more complicated, as is evident in fig. 6.7(a). The volatility initially rises, reaching a maximum at $\lambda_{\max} \approx 2$ and then falls, although never to the low level of the unregulated case.

The explanation for the initial rise in volatility comes from the fact that for $\lambda_{\max} = 1$ there is no short selling possible, see eq. (6.5). In this case there are long-only funds only. As $\lambda_{\max} = 2$, funds now also engage in short selling and we experience an effective regime-shift from a long-only to a long-and-short model. Note that the average leverage for the Basle II regime (fig. 6.7(c)) is below 1, meaning that there are often cases where there is no leverage. In those situations where a leverage reduction from $\lambda > 1$ to $\lambda = 1$, fund managers are forced out of short positions leading to do extra trading activity (that does not exist for the $\lambda_{\max} = 1$ case) that slightly raises the volatility.

The behavior of the perfect hedge scheme is also more complicated; it initially falls until $\lambda_{\max} \sim 10$, but then rises again. The reason for the increase in volatility for large $\lambda_{\max}$ under the perfect hedge scheme is that for high maximum leverage the effective borrowing costs are large, as illustrated in fig. 6.7(d). This is also the reason why in this scheme the trading volume drops for $\lambda_{\max} > 10$. (See eq. (6.17) and eq. (6.28)). For the unregulated case the borrowing costs are zero (since for convenience we set the base interest rate to zero), whereas under the Basle II scheme they are fixed. In the perfect hedge scheme the costs are near zero for small leverage and then grow sharply starting at about $\lambda_{\max} \approx 5$, and exceed the costs for the Basle II scheme at about $\lambda_{\max} \approx 12$. Thus the perfect hedging scheme is cheaper than the Basle II scheme for low leverage and more costly for high leverage.

Figure 6.7(c) shows the average effective leverage of fund managers, defined as

$$\langle \lambda_h(t) \rangle = \frac{1}{HT} \sum_{h=1}^{H} \sum_{t=1}^{T} \lambda_h(t).$$

For the unregulated case, as expected, the average leverage initially increases as $\lambda_{\max}$ increases. It rises from $\langle \lambda_h(t) \rangle \approx 0.4$ when $\lambda_{\max} = 1$ to a little less than two when $\lambda_{\max} \approx 5$. Surprisingly, however, it then decreases until about $\lambda_{\max} \approx 10$, settling into a plateau for $\lambda_{\max} > 10$ with $\langle \lambda_h(t) \rangle \approx 1.5$. The reason for the decrease is the drop in volatility, which means that there are fewer mispricings and less opportunities to use leverage. The Basle II and perfect hedge schemes behave similarly, except that they drop very little after their peaks, which are reached at larger $\lambda_{\max}$, and their plateau leverage is higher, with $\langle \lambda_h(t) \rangle \approx 2$.

Figure 6.8 shows a variety of diagnostics about market performance, including (a) the probability of fund default, (b) return to investors, (c) profits for fund managers and (d) capital shortfall of banks.

Figure 6.8 (a) shows the average annual probability of default for the most aggressive fund manager. In the unregulated scheme the annual probability of default initially grows rapidly, but then reaches a plateau at $\lambda_{\max} \approx 8$. The reason for this is that under the unregulated scheme the use of leverage is automatically self-limiting due to dropping volatility, as demonstrated in fig. 6.7(c). For the Basle II and perfect hedge schemes the initial rise in defaults is slower, but unlike the unregulated case the default rate never plateaus, and default exceeds the unregulated scheme for roughly $\lambda_{\max} > 11$. The reason that there are more defaults in both regulated schemes is that the maximum leverage is adjusted dynamically. If the maximum leverage is suddenly decreased when funds are at their maximum leverage, they are forced to sell *en masse*, and the resulting market impact can trigger a crash[9]. In fig. 6.8(b) we show the average adjusted rate of return r^{adj} to fund investors for the most aggressive fund manager. The return to fund investors is influenced

[9] For $\lambda_{\max} < 10$ the perfect-hedge scheme performs a bit better than the Basle II scheme because of the stronger limit to lending based on historical volatility illustrated in fig. 6.3.

mainly by three factors: effective leverage, mispricing opportunities and probability of fund default. In each of the three regulatory schemes the investor returns behave similarly, initially increasing with $\lambda_{\max}$, reaching a peak, and then decreasing. Under the Basle II and perfect hedge schemes the peaks come later: For the unregulated scheme the peak is at $\lambda_{\max} \approx 4$, for the perfect hedge scheme it is at $\lambda_{\max} \approx 6$, and for Basle II it is at roughly $\lambda_{\max} \approx 8$. The primary reason there is a peak is the rising default rate[10]. Another important factor is decreased volatility, and hence fewer mispricings and lower effective leverage. For large $\lambda_{\max}$ the perfect hedge case behaves increasingly poorly due to sky-rocketing borrowing costs (see fig. 6.7(d)).

Figure 6.8(c) shows the fund managers' profits. We assume a hypothetical 2% fixed fee for the assets under management and a 20% performance fee. Profits to funds are consistently higher in the unregulated scheme than in either of the alternatives. The discrepancy is exaggerated relative to investors' profits due to the fact that under the unregulated scheme the assets under management by the funds are much larger. It is perhaps not surprising that fund managers clearly prefer less regulation. Surprisingly, as $\lambda_{\max}$ increases from one to two, fund managers' profits initially drop; for the unregulated case it reaches a minimum about 30% less than the unleveraged case, which for the regulated schemes is almost 75%. The origin of this problem is the same as mentioned above, that for $\lambda_{\max} = 1$ it is not possible to short sell, see eq. (6.5). In this case we have long-only funds. As soon as we bring leverage to $\lambda_{\max} = 2$, funds engage in short selling and we have a shift from a long-only to a long-and-short model. We have explicitly checked this issue by tests, where we make the demand function for short selling eq. (6.5) fully symmetric to the long-part, by removing the 1 in eq. (6.5). In this case no more drop in the managers' profits from $\lambda_{\max} = 1$ to $\lambda_{\max} = 2$ occurs. Note that this symmetric implementation is of course not the correct one. Profits are consistently higher for the perfect hedge scheme than they are in the Basle II scheme.

Finally, in fig. 6.8(d) we show the capital shortfall of banks. As expected, the shortfall is the largest for the unregulated case, and for the perfect hedge case it is zero by definition.

[10] If funds that have gone bankrupt are excluded the performance reaches a maximum at $\lambda_{\max} \sim 7$.

6.5 Implications of the regulation schemes for economics and society

In this chapter we studied an agent based model of a financial market where investors have different degrees of information about the fundamental value of financial assets. Fund managers leverage their investments by borrowing from banks. These speculative investments based on credit introduce a systemic risk component to the system. When the collateral backing the involved loans are composed of the same financial assets themselves, the model reproduces the various stages of the leverage cycle, [176, 177, 27, 28], and the systemic prerequisites leading up to crashes can be studied in detail, [31]. In this chapter we have studied the role of Basle II-type regulations, which define the conditions under which banks can provide leverage. These regulations basically require banks to apply haircuts to the collateral accepted, and to take spreads. This raises the capital costs for the leverage takers, so that they take less effective leverage than they would in the unregulated case. We find that this is indeed the case for situations of low leverage in the system; regulation makes the system more secure. On the other hand regulation reduces the market share of fund managers in general, with the consequence that they take less volatility from the markets than they would in the unregulated case. In this sense there is no optimal level of leverage or optimal level of regulation. Regulation makes the markets more secure in the sense that it reduces the frequency of large price jumps, but renders markets more volatile in general.

The situation changes drastically when the general level of leverage is high in the system, which is the case for phases of low volatility. When the leverage is greater than about 10, investors in the regulated schemes take more effective leverage than they would in an unregulated world. This is easy to understand: in the unregulated situation the fund managers become bigger (in the model up to twice as big in terms of assets under management) and hence reduce volatility more effectively. In this scenario the regulated system becomes less stable than the unregulated one, which is for example reflected in a higher default rate of regulated investors than unregulated ones. Also the regulated system does not manage to reduce the frequency of crashes. In terms of capital shortfall of banks, the regulated system is superior to the unregulated one for all leverage levels in the system.

We next designed a hypothetical regulation system, where banks require their investors to hedge against the risk of loss of collateral value. Under the assumption that the writers of options never default, by construction the capital shortfall of banks is zero. This regulation scheme tests the effect of making the capital costs (effective interest rate) for the fund managers dependent on the actual leverage taken; capital for higher leverage (and thus more systemic risk) is more expensive. This is not the case for Basle II-type regulation, where the interest rate is independent of leverage.

Even under the perfect hedging scheme the system does not get much safer on a systemic level. The effects are qualitatively and quantitatively similar to the Basle II-type scenario. However, in terms of volatility reduction the perfect-hedge scheme is shown to be superior to the Basle II scheme.

We have thus demonstrated that even under the assumption of a perfect-hedge scheme, systemic risk originates from a source that is not addressed by present regulation mechanisms. Systemic risk arises due to a synchronization of the agents' behavior in times of high leverage. Such synchronized behavior can become worse under regulation. This is because a lowering of the maximum leverage at a point where some of the funds are fully leveraged can cause a wave of selling, driving prices down and triggering even more selling, and in some cases leading to a crash.

As shown in chapter 5 systemic risk is not only related to network properties but it is a multiplex network concept. By this we mean that systemic risk happens on various layers of the financial system, which can all influence each other. The networks involved include: borrowing and lending relationships (which can be further broken down into explicit contractual obligations, i.e. counterparty exposures, and implicit relationships, such as roll-over of overnight loans), insurance (derivative) contracts, collateral obligations, market impact of overlapping asset portfolios and network of cross-holdings (holding of securities or stocks of fellow banks).

In this chapter we do not propose a solution to the problem of credit regulation. However, our belief is that a key element of any such regulation should be greater transparency. As argued in [163], one can imagine a system where every credit provider has to disclose the amount of its loans and the identity of the borrower on their homepage, and borrowers would have to disclose their leverage. In this way there would develop a transparent credit market with emerging lending rates, depending on the riskiness of the creditor and the borrower. Consequences of such schemes are presently under investigation.

Chapter 7

Controlling systemic risk in financial networks by increased transparency

7.1 The problem of in-transparent interactions in financial networks

Since the beginning of banking the possibility of a lender to assess the riskiness of a potential borrower has been essential. In a rational world, the result of this assessment determines the terms of a lender-borrower relationship (risk-premium), including the possibility that no deal would be established in case the borrower appears to be too risky. When a potential borrower is a node in a lending-borrowing network, the node's riskiness (or creditworthiness) not only depends on its financial conditions, but also on those who have lending-borrowing relations with that node. The riskiness of these neighboring nodes depends on the conditions of their neighbors, and so on. In this way the concept of risk loses its local character between a borrower and a lender, and may become *systemic*. A systemically risky node in a financial network is one that – should it default – will have a substantial impact (losses due to failed credits) on other nodes in the network. Note that this notion of *systemic risk* is different from the risk of not getting payed back, the *credit default risk*.

The assessment of the systemic riskiness of a node turns into an assessment of the entire financial network [21]. Such an exercise can only be carried out with information on the asset-liability network. This information is, up to now, not available to individual nodes in that network. In this sense, financial networks – the interbank (IB) market in particular – are opaque. This in-transparency makes it impossible for individual banks to make rational decisions on lending terms in a financial network, which leads to a fundamental principle: opacity in financial networks rules out the possibility of rational risk assessment, and consequently, transparency, i.e. access to system-wide information is a necessary condition for any systemic risk management. Note that recently an alternative notion for systemic importance of banks for the fluid transmission of credit through the IB market has been discussed in terms of "controllability" [178].

The banking network is a fundamental building block in our globalized society. It provides a substantial part of the funding and liquidity for the real economy [179]. The real economy – the ongoing process of invention, production, distribution, use, and disposal of goods and services – is inherently risky and introduces a third type of risk, the *economic risk*. This risk originates in the uncertainty of payoffs from investments in business ideas, which might not be profitable, or simply fail. This economic risk can not be eliminated from an evolving economic system, however it can be spread, shared, and diversified. One of the roles of the financial system is to distribute the risk generated by the real economy among the actors in the financial network. The financial network can be seen as a service to share the burden of economic risk. By no means should this service by itself produce additional systemic risk on top of economic risk endogenously. Neither should the design and regulation of financial networks introduce mechanisms that leverage or inflate the economic risk. As long as systemic risk is endogenously generated within the financial network, this system is not yet properly designed and regulated. In this chapter we show that, unless a certain level of transparency is introduced in financial networks, systemic risk will be endogenously generated within financial networks. Systemic risk is hard to reduce with traditional regulation schemes [31, 2]. By introducing a minimum level of transparency in financial networks, endogenous risk can be drastically reduced without negative effects on the efficiency or volume in the financial services for the real economy. We think that the following results on systemic risk management hold generally. However, for demonstration purposes we use a specific setup of banks in the IB network that finance demands from the real economy.

Asset-liability or exposure data needed for systemic risk assessment in actual financial networks such as the IB market, does exist on various levels of reliability. In some developed countries IB loans are directly recorded in the "central credit register" of central banks, [34, 180]. In several countries the exposure matrix can be estimated from IB payment data, as in [181, 37].

The capital structure of financial agents, which is also necessary for systemic risk assessment, is available in most countries through standard reporting to central banks. Payment systems record financial flows with a time resolution of one second, see e.g. [182]. Several studies have been carried out on historical data of asset-liability networks [34, 33, 24, 36, 37, 35], including overnight markets [40], and financial flows [38]. However, exposure networks, payment flows and balance sheets do not yet provide a complete picture. For a more complete view on the actual risk networks it would be necessary to integrate data of credit derivative (issuer-holder) networks, and collateral networks (who holds what collateral for what loan). The true risk network is a multiplex network where the same set of financial agents is connected by various networks, including the asset-liability network, the derivative and the collateral network, posing significant data challenges. For simplicity, in this work we assume that it is possible (for central banks) to compute network metrics based on the asset-liability matrix at any time (as a proxy of the true systemic risk network), which in combination with the capital structure of banks, allows to define a *systemic risk-rating* of banks.

Network metrics can be used to systematically capture the fact that systemic risk spreads by borrowing. Borrowing from a systemically risky bank makes the borrower systemically more risky, since its default might tip the risky lender into default which then may cause system wide effects. These metrics are inspired by PageRank, where a web page, that is linked to a famous page, gets a share of the "fame". A metric similar to PageRank, the so-called DebtRank, has been recently used to capture systemic risk levels in financial networks [98]. In this chapter we present an agent based model of the IB network that allows to estimate the extent to which systemic risk can be reduced by introducing transparency on the level of the DebtRank. For computational efficiency we propose a measure based on Katz centrality [114], which we refer to as Katz rank. Both are closely related to the concept of eigenvalue centrality [183]. Betweenness centrality has been used to determine systemic financial risk before [24]. To demonstrate the risk-reduction potential of feeding information of the DebtRank back into the system, we use a simple toy model of the financial- and real economy which is described in the next section. Interbank models of similar design were used before in different contexts [184, 25, 185].

The central idea of this chapter is to operate the financial network in two modes. The first reflects the situation today, where banks don't know about the systemic impact of other banks, and where all IB credits are traded with the same interest rate, the so-called "inter bank offer rate", r^{ib}. We call this scenario the *normal mode*.

The second mode introduces a minimum regulation scheme, where banks choose their IB trading partners based on their DebtRank. The philosophy of this scheme comes from the fact that borrowing from a systemically dangerous node can make the borrower also dangerous, since she inherits part of the risk, and thereby increases overall systemic risk. Note, that a default of the borrower from a systemically dangerous bank affects not only the lender, but possibly also all other nodes from which the lender has borrowed. The idea is to reduce systemic risk in the IB network by not allowing borrowers to borrow from risky nodes. In this way systemically risky nodes are punished, and an incentive for nodes is established to be low in systemic riskiness. Note, that lending *to* a systemically dangerous node does *not* increase the systemic riskiness of the lender. We implement this scheme by making the DebtRank of all banks visible to those banks that want to borrow. The borrower sees the DebtRank of all its potential lenders, and is required (that is the regulation part) to ask the lenders for IB loans in the order of their inverse DebtRank. In other words, it has to ask the least risky bank first, then the second risky one, etc. In this way the most risky banks are refrained from (profitable) lending opportunities, until they reduce their liabilities over time, which makes them less risky. Only then will they find lending possibilities again. This mechanism has the effect of distributing risk homogeneously through the network, and prevents the emergence of systemically risky nodes in a self-organized critical way: risky nodes reduce their credit risk because they are blocked from lending, non-risky banks can become more risky by lending more. We call this mode the *transparent mode*.

7.2 A model to study the effects of transparency on systemic risk – a simplified CRISIS model

The agents in the model are B banks, F firms and households. For simplicity every bank has only one firm as commercial client, $F = B$. This simplification is to some extent justified by the fact that for example in Germany the number of large corporations and the number of relevant banks are of the same order of magnitude. In fig. 7.1 we show a schematic structure of the model. At every time step each firm approaches its main bank with a request for a loan. The size of these loans is a random number from a uniform distribution. Banks try to provide the requested firm-loan. If they have enough cash reserves available, the loan is granted. If they do not have enough, they approach other banks

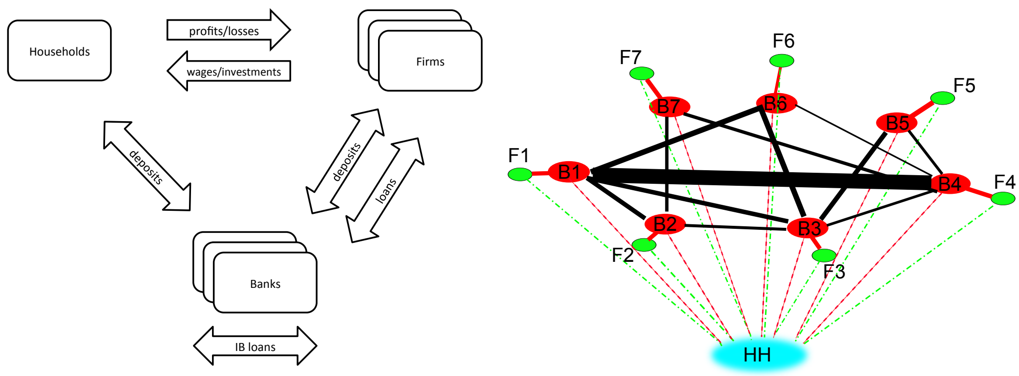


Figure 7.1: Schematic structure of the model: firms approach their bank for firm-loans. These loans are transferred to the households, where they are redistributed to other firms or are deposited in banks. If a bank can not service a firm-loan because it presently does not have the requested sum available in the bank, it tries to get the necessary funding through an interbank loan from an other bank. If it can get an IB loan, the firm-loan is payed out, if it can not, the firm will receive no loan.

in the IB market and try to get the amount from them at an interest rate of r^{ib}. Not every bank has business relations with every other bank. Interbank relations are recorded in the IB *bank-relation network*, A. If two banks i and j, are willing to borrow from each other, $A_{ij} = 1$, if they have no business relations, $A_{ij} = 0$. We model the IB relation network with fully connected networks, random graphs and scale-free networks, see paragraph 7.2.2.0.1. A fully connected bank-relation network means that $A_{ij} = 1$, for all pairs (i, j). In this case any bank can do business with any other and there is no special network topology or bias in business relations. If a bank does not have enough cash and can not raise the full amount for the requested firm-loan on the IB market, it does not pay out the loan. If the bank does pay out a loan, the firm transfers some of the cash to the households as "investments" for future payoffs (wages, invest in new machines, etc.). Loans from previous time steps are paid back after τ time steps with an interest rate of $r^{\mathrm{f-loan}} > r^{\mathrm{ib}}$. The fraction of the loan not used to pay back outstanding loans, ends up at the households.

Households use the money received from firms to (1) deposit a certain fraction at the bank, for which they get interest of r^{h}, or (2) to consume goods produced by other firms. This money flows back to firms (the firms' profits) and is used by those to repay loans. If firms run a surplus, they deposit it in their bank accounts, receiving interest of $r^{\mathrm{f-deposit}}$. The two actions of the households effectively lead to a re-distribution and re-allocation of funds at every time step. For simplicity we model the households as a single (aggregated) agent that receives cash from firms (through firm-loans) and re-distributes it randomly in banks (household deposits), and among other firms (consumption).

Specifically, at time t a bank-firm pair is chosen randomly, and the following actions take place:

(i) banks and firms repay loans issued at time $t - \tau$

(ii) firms realize profits or losses (consumption)

(iii) banks pay interest to households

(iv) firms request loans

(v) households re-distribute cash obtained from firms

(vi) liquidity management of banks in the IB market, including: IB repayments, firm-loan requests, defaulted firms, and re-distribution effects from households

(vii) firms pay salaries and make investments

(viii) firms or banks default if equity or liquidity problems arise

A new bank-firm pair is picked until all are updated (random sequential update); then time step $t + 1$ follows.

During the simulation firms and banks may be unable to pay their debts and thus become insolvent. Firms are declared bankrupt if they are either insolvent, or if their equity capital falls below some negative threshold. Banks are declared bankrupt if they are insolvent, or have equity capital below zero. Negative equity of firms can result from a large loss (households do not buy there) or a series of losses on its investments. Negative equity of banks can arise through the bankruptcy of a firm or another bank and the subsequent failure of their loan repayments. If a firm goes bankrupt the bank writes off the respective outstanding loans as defaulted credits and realizes the *losses*. If the bank has not enough equity capital to sustain these losses it goes bankrupt as well. After the bankruptcy of a bank there occurs a default-event for all its IB creditors. This may trigger a cascade of bank defaults. For simplicity, there is no recovery for IB loans. This assumption is reasonable for the short run, which matters in practice for short term liquidity [73]. A cascade of bankruptcies happens within one time step. After the last bankruptcy is taken care of, the simulation is stopped. We model a *closed* system of banks, firms and households, meaning that there are no in- or out-flows of cash from the model.

7.2.1 The agents and their properties/states

7.2.1.0.1 Firms Every time step each firm performs the following tasks in the following order

- repay loans to banks
- file a (random) loan request to their bank (for investments, paying wages, etc.)
- realize random profits or losses from previous investments
- receive the loan (or not) and make investments and pay salaries to households.

The firm's *investments*, are

$$I_i(t) = \sum_{t'=0}^{\tau} a_i(t-t'), \tag{7.1}$$

where $a_i(t)$ is the amount the firm invests at time t and pays to the households. These investments are tracked for τ time steps, because for simplicity we assume the firm i makes a random return (profit or loss) τ time steps later.

The firm's *cash* is deposited in the bank account of firm i. The size of the deposit at time t is $D_i(t)$. For these deposits the firms receive an interest rate of $r^{\text{f}-\text{deposit}}$.

The *liabilities* of a firm are loans received (and accumulated over time) from its bank, $L_i^{\text{f}}(t)$. For simplicity, all loans have the same maturity of τ time steps. The total amount of loans received by firm i (from bank i) at time t is

$$L_i^{\text{f}}(t) = \sum_{t'=0}^{\tau} l_i(t-t'), \tag{7.2}$$

where $l_i(t)$ is the size of the loan payed out at t. The *equity* of firm i is obtained by subtracting its liabilities from its cash and assets

$$C_i^{\text{f}}(t) = D_i(t) + I_i(t) - L_i(t), \tag{7.3}$$

At every time step all firms file new loan requests to their banks. The loan request of firm i follows a random process

$$l_i^{\mathrm{req}}(t) = \zeta_t - \min[0, D_i(t)], \tag{7.4}$$

where ζ_t is the realization of an i.i.d. random number from a uniform distribution between zero and α, which is fixed at some constant (same for all i). The "min" is present to ensure that the deposits of a firm are never negative. If the bank of firm i has enough cash reserves available the loan request will be immediately granted and payed out,

$$l_i(t) = \begin{cases} l_i^{\mathrm{req}}(t) & \text{if } R_i(t) \geq l_i^{\mathrm{req}}(t) \\ -\min[0, D_i(t)] & \text{if } l_i^{\mathrm{req}}(t) > R_i(t) \geq -\min[0, D_i(t)] \\ 0 & \text{otherwise.} \end{cases} \tag{7.5}$$

Here $R_i(t)$ is the reserves of bank i (see paragraph 7.2.1.0.3). The firm pays and interest rate of $r^{\mathrm{f-loan}}$ for the loan. For simplicity, we fix the interest rate $r^{\mathrm{f-loan}}$ to be the same for all firms, see table 7.1. This is of course a somewhat unrealistic assumption. Interest rates for firm loans vary across banks and firms and reflect perceived risks of firms. More realistic heterogeneity of firm interest rates alone would favor profitable, and punish loss-making firms. Banks requiring low interest rates would have lower earnings. Since every bank has only one firm as a customer, banks offering low interest rates would not earn enough. A consistent natural extension to the model would therefore be to introduce an adaptive interest scheme such as in [130], and at the same time a market for these loans, so that every bank could serve multiple firms. This is one of the aims of the FP7 CRISIS[1] model but beyond the scope of this work.

If the bank of firm i has not enough cash reserves to grant the loan request, the bank at least tries to grant a loan to balance the deposit account of the firm. If the reserves of the bank are not sufficient for this, the bank does not grant a loan.

If the firm receives the loan, the corresponding cash is "invested" (think of paying workers, buying new machines, etc.).

$$a_i(t) = \max[0, l_i(t) - \min[0, D_i(t)]]. \tag{7.6}$$

Again, the min and max ensure that the firm does not invest more cash than it has. On these investments, firm i makes a random return (profit or loss) τ time steps later.

$$p_i(t) = \xi_i a_i(t - \tau), \tag{7.7}$$

[1] `http://www.crisis-economics.eu`

where $\xi_i \in \mathcal{N}(\mu_i, \sigma^{\text{return}})$, i.e. an i.i.d. random number from a normal distribution with mean μ_i and standard deviation σ^{return}. Each firm starts with an initial equity of $C_i^{\text{f}}(0) = 1$. Their deposits evolve as

$$D_i(t) = (1+r^{\text{f}-\text{deposit}})D_i(t-1)-(1+r^{\text{f}-\text{loan}})l_i(t-\tau)+l_i(t)+p_i(t)-a_i(t). \quad (7.8)$$

A firm goes bankrupt in either of two cases: (i) its equity falls below a (negative) threshold $C_i^{\text{default}} = -15$ or (ii) its liquidity is below zero, $D_i(t) < 0$. Negative equity can be the result of a large loss or a series of losses on its investments. Liquidity problems of firms arise when banks do not receive loans from their main bank, i.e. when the bank does not have enough reserves or is unable to raise enough liquidity on the interbank market (see section 7.2.2). In both cases the firm is declared bankrupt and goes out of business.

If a firm i goes out of business it "sells" its assets $I_i(t)$ to the households to repay as much as possible of the debt to the bank. This means that

$$D_j^{\text{h}}(t) = D_j^{\text{h}}(t) - w_j(t)I_i(t) \quad (7.9)$$

and

$$D_i^{\text{f}}(t) = D_i^{\text{f}}(t) + I_i(t). \quad (7.10)$$

Here $D_j^{\text{h}}(t)$ are the deposits of households and $w_j(t)$ is the relative fraction of household deposits at bank j, see paragraph 7.2.1.0.2 for details. The main bank of the firm gets the remaining funds and writes off the outstanding debt of the bankrupt firm. If a firm defaults at time t we set $I_i(t) = 0$, $D_i(t) = 0$ and $L_i^{\text{f}}(t) = 0$.

7.2.1.0.2 Households The role of households in the model is to provide a re-allocation and re-distribution mechanism of the economy. Households receive money for labour from their firms, they buy products from other firms, make deposits at banks (which are not necessarily the same as the main bank of their firm), etc. For simplicity, households are modeled as a single representative agent. They hold a bank account at every bank. We denote the deposits the households hold at bank i at time t by $D_i^{\text{h}}(t)$. The relative fraction of household deposits at bank i (i.e. the market share in total deposits of the bank) is $w_i(t) = D_i^{\text{h}}(t)/\sum_i D_i^{\text{h}}(t)$. These fractions change stochastically over time. We model these changes as a slowly mean-reverting random process, where the deposits mean revert around a market share of $1/B$ (B is the number of banks),

$$\tilde{w}_i(t) = \rho\tilde{w}_i(t-1) + \chi_i(t) + (1-\rho)\frac{1}{B}, \quad (7.11)$$

where χ_i is from an i.i.d. normal distribution $N(0,\sigma)$. With normalization after every realization the market shares are $w_i(t) = \tilde{w}_i(t)/\sum_{i=1} \tilde{w}_i(t)$. For $\rho < 1$, $w_i(t)$ mean-reverts around $1/B$, and for appropriate choices of σ, the positivity of $w_i(t)$ can be ensured for all practical purposes. The deposits of the households at bank i evolve as

$$D_i^{\mathrm{h}}(t) = w_i(t) \sum_{i=1}^{B} \left[(1+r^{\mathrm{h}})D_i^{\mathrm{h}}(t-1) - p_i(t) + a_i(t)\right] , \tag{7.12}$$

where r^{h} is the interest rate for these deposits. Deposits of the households are *demand deposits* which can be withdrawn at any time.

7.2.1.0.3 Banks Every bank i has only one firm i as a customer. At each time step banks perform the following tasks:

- collect deposits from households and pay interest at the rate r^{h} for last time step
- hold deposits of firms
- issue new loans to firms at the interest rate $r^{\mathrm{f-loan}}$
- borrow or lend in the interbank market at the interest rate r^{ib}

Banks collect deposits from firms and households and provide loans to firms. The *assets* of bank i are its cash reservers $R_i(t)$ plus the total loans provided to firms, $L_i^{\mathrm{f}}(t)$, and loans to other banks. For IB loans we assume the same time to maturity τ (same duration as firm loans), so that the total outstanding interbank loans of bank i are

$$L_i^{\mathrm{IB}}(t) = \sum_{t'=0}^{\tau} \sum_{j=1}^{B} l_{ji}(t-t'), \tag{7.13}$$

Note that the entries in $L_{ij}(t) = \sum_{t'=0}^{\tau} l_{ij}(t-t')$ are the liabilities bank i has towards bank j at time t. We use the convention to write liabilities in the rows (second index) of l. If the matrix is read column-wise (transpose of l) we get the assets or claims, banks hold with each other. The *liabilities* of bank i are the deposits of firms $D_i^{\mathrm{f}}(t)$, deposits of households $D_i^{h}(t)$, and IB loans from other banks $B_i^{\mathrm{IB}}(t)$,

$$B_i^{\mathrm{IB}}(t) = \sum_{t'=0}^{\tau} \sum_{j=1}^{B} l_{ij}(t-t'). \tag{7.14}$$

The equity of a bank is given by subtracting its liabilities from its assets,

$$C_i^{\mathrm{b}}(t) = R_i(t) + L_i^{\mathrm{IB}}(t) + L_i^{\mathrm{f}}(t) - B_i^{\mathrm{IB}}(t) - D_i(t) - D_i^{\mathrm{h}}(t). \tag{7.15}$$

Banks are the only agents in the model that keep cash reserves. All other agents always deposit their cash in bank accounts. The reserves of banks only change through interbank loans, or, if agents with bank accounts at different banks conduct mutual business, e.g. think of households buying products at different firms which then make a profit and deposit that cash at their bank accounts. However, if a firm receives a loan from its main bank this does not affect the cash reserves of the bank. Each bank starts with an initial reserve $R_i(0) = 1$, which evolves according to

$$R_i(t) = R_i(t-1) + \Delta L_i^{\mathrm{IB}} + \Delta B_i^{\mathrm{IB}} + \Delta D_i^{\mathrm{h}}(t), \tag{7.16}$$

with

$$\begin{aligned} \Delta L_i^{\mathrm{IB}} &= (1 + r^{\mathrm{ib}}) \sum_j l_{ji}(t-\tau) - \sum_j l_{ji}(t), \\ \Delta B_i^{\mathrm{IB}} &= \sum_j l_{ij}(t) - (1 + r^{\mathrm{ib}}) \sum_j l_{ij}(t-\tau), \\ \Delta D_i^{\mathrm{h}}(t) &= D_i^{\mathrm{h}}(t) - D_i^{\mathrm{h}}(t-1). \end{aligned} \tag{7.17}$$

The equity of a bank is not affected by a change in its reserves. It changes only as a consequence of interest payments or because of credit defaults of firms or other banks.

A bank goes bankrupt if either its equity $C_i(t)$ or reserves $R_i(t)$ become negative. Negative equity can be triggered by the bankruptcy of a firm. Liquidity problems can occur when banks are unable to raise enough liquidity on the interbank market. There is no recovery of IB loans considered, and lending banks write off the loans extended to the defaulted banks.

7.2.2 The interbank network

Banks can borrow or lend from other banks on the interbank market at interest rate r^{ib}. Constant IB interest for all banks is a simplification that is not fully realistic. It is especially invalid in times of turmoil. For feasibility however, we make this simplification and intend to study the potentially important systemic effects of heterogeneous IB interest rates by an extension of this model in a separate work within the FP7 CRISIS framework. Whether two banks consider lending to each other, is specified with the interbank network A. We refer to A as the (symmetric) *bank-relation network*. $A_{ij} = 1$ means that bank i would in general consider lending to- and borrowing from bank j, they have a business relation, and $A_{ij} = 0$ means that i and j have no business relations. If a bank needs additional liquidity (for servicing a firm-loan request) it contacts other banks with which it is connected in the IB network, and issues an IB loan request. It contacts its neighbors in the IB network until the liquidity requirements are satisfied. Note that the order in which these IB loan requests are made on the IB market is random in the normal mode, and follows the ordering according to Debt- or Katz rank in the transparent scheme (the least risky bank is approached first). The IB loan request of bank i is of a size such that an external firm-loan request can be serviced,

$$l_{\mathrm{i}}^{\mathrm{IB-req}}(t) = \max\left[0, l_{\mathrm{i}}^{\mathrm{req}}(t) - R_{\mathrm{i}}(t)\right]. \tag{7.18}$$

The contacted bank j will grant the requested loan if it has enough liquidity available. The amount bank i has finally borrowed from bank j at time t is

$$l_{ji}(t) = \begin{cases} 0 & \text{if } R_j(t) - l_j^{\mathrm{req}}(t) \leq 0 \\ l_{\mathrm{i}}^{\mathrm{IB-req}}(t) & \text{if } R_j(t) - l_j^{\mathrm{req}}(t) \geq l_{\mathrm{i}}^{\mathrm{IB-req}}(t) \\ R_j(t) - l_j^{\mathrm{IB-req}}(t) & \text{otherwise.} \end{cases} \tag{7.19}$$

Note that the loan size depends on the firm-loan extended to firm j in that time step. In case the first contacted bank j can not provide the full requested liquidity the requesting bank i takes a smaller amount $(l_{ji}(t) \leq l_{\mathrm{i}}^{\mathrm{IB-req}}(t))$ and continues by asking the set of other banks it has connections to, $\{j \mid A_{ij} = 1\}$, for the remaining funds.

7.2.2.0.1 The interbank network topology For the bank-relation network A we use two types of networks in our simulations, random graphs of Erdös-Rényi type (ER), and for comparison the more realistic, scale free (SF) networks [34]. For the ER networks we specify the linking probability [107], for any pair of the B banks by $0 < \gamma \leq 1$. The SF networks are produced with the Barabási-Albert preferential attachment algorithm [110], using $m = 6$ links, with which any new node is linked to the existing network. If simulations are carried out repeatedly with the same parameters, we generate for each simulation a new bank-relation network.

In our simulations we find the distributions of IB loans $(l_{ji}(t))$, within the range from approximately 0 to 10. The distribution itself is an approximate power law with a slope of about -2, which it is not incompatible with empirical values [34] (not shown).

Table 7.1: List of the parameters and initial values as used in the model.

number of banks and firms	$B = F = 100$
interest rate for IB market	$r^{\mathrm{ib}} = 0.0008$
interest rate for deposits of households	$r^{\mathrm{h}} = 0.00085$
interest rate for deposits of firms	$r^{\mathrm{f-deposit}} = 0.0001$
interest rate for loans to firms	$r^{\mathrm{f-loan}} = 0.001$
mean reversion parameter in re-allocation process	$\rho = 0.99$
standard deviation for re-allocation process	$\sigma = 0.0001$
upper limit for loan requests of firms	$\alpha = 3$
mean return of firms on loans	$\mu_{\mathrm{i}} = 1.01$
standard deviation of firm returns	$\sigma^{\mathrm{return}} = 0.3$
initial deposits of households	$D_i^{\mathrm{h}}(0) = 3$
initial equity of banks	$C_i^{\mathrm{b}}(0) = 1$
initial equity of firms	$C_i^{\mathrm{f}}(0) = 1$
ER linking probability if IB network	$\gamma = [0.115, 0.25, 1]$
SF network parameter (number of links per new node)	$m = 6$

7.2.3 The parameters of the model

All parameters of the model are collected in table 7.1. The simulations for the comparisons of Katz vs. DebtRank, SF vs. ER, and different connectivities, were run with different initial random number seeds. For any realistic situation we assume that $r^{\mathrm{f-loan}} > r^{\mathrm{h}} > r^{\mathrm{ib}} > r^{\mathrm{f-deposit}}$.

7.3 Regulation schemes with various levels of transparency

7.3.1 The unregulated scheme

In the normal mode the model captures the current market practice, where banks follow a simple strategy to manage their liquidity. If a bank needs additional liquidity (for providing a firm-loan request, or for its own re-payments of IB loans) it contacts banks it is connected with in the IB relation network A, and asks them for IB loans. In the normal mode, bank i asks its neighbors j (with $j \in \mathcal{I}_i = \{j' \mid A_{ij'} = 1\}$) in *random* order. If bank j can provide only a fraction of the requested IB loan, bank i takes it, and continues to ask an other neighbor bank from $\mathcal{I}_i$ (in random order) until the liquidity requirements of i are satisfied.

7.3.2 The transparent interbank mode

A simple modification to improve the stability of the system is to avoid borrowing from banks with a large systemic impact. For this a minimum level of transparency of the IB market is necessary. For all banks we compute systemic risk metrics based on the IB liability network $L_{ij}(t)$, and the equity of banks $C_i^{\mathrm{b}}(t)$, at time step t. In particular we compute the DebtRank R_i^{debt} [98], and – for comparison – the Katz rank R_i^{katz}. The most risky bank has rank 1, the least risky has rank B.

The Katz centrality can be used to capture the risk of contagion in IB networks and is defined as

$$K_i = \alpha \sum_j L_{ij} K_j + \beta, \tag{7.20}$$

To ensure that the Katz centrality converges, we set $\alpha = 1/\kappa_1$, where κ_1 is the largest eigenvalue of L_{ij}. The overall multiplier β is not important, for convenience we set $\beta = 1$. We define the *Katz rank* in the following way: the most risky bank i, with the highest Katz centrality gets Katz rank $R_i^{\mathrm{katz}}(t) = 1$, the least risky bank j (lowest Katz centrality) gets $R_j^{\mathrm{katz}}(t) = B$. Note, that banks that only borrow (in-links only) may cause contagion and have non-zero Katz centrality. Banks that only provide loans (out-links) have zero Katz centrality. Loan sizes, neighbors and their neighbors, etc., are included in the centrality.

In contrast to the normal mode, before bank i asks its neighbors for IB loans, it orders them (the banks contained in set $\mathcal{I}_{\mathrm{i}}$) according to their inverse Debt- or Katz rank. It then asks its neighboring banks in the order of their inverse rank, i.e. it first asks the least risky, then the next risky, etc. The rank is computed at the beginning of each time step. In this way the low-risk banks are favored because the likelihood for obtaining (profitable) IB deals is much higher for them than for risky banks, which are at the end of the list and will practically never be asked.

In reality this implies that the banks know the DebtRank of each of their neighboring banks. This transparency is not available in the present banking system. Note however, that in many countries central banks have all the necessary data to compute the DebtRank. A possible way to implement such an incentive scheme in reality is presented in the discussion.

We further implement a version of the transparent IB market where the DebtRank is computed after every transaction that takes place in the IB market, instead of being computed at the beginning of the day. This version we refer to as the *fast mode*.

7.4 The impact of increased transparency on systemic risk

7.4.1 Results for measures of systemic risk

For measures of systemic risk in the system, we use the following three observables: (1) *time to first default* as the time steps of the simulation before the first default of a bank occurs, $\mathcal{T}^{\mathrm{fd}}$, (2) the *size of the cascade*, $\mathcal{C}$ as the number of defaulting banks triggered by an initial bank default ($1 \leq \mathcal{C} \leq B$), and (3) the *total losses to banks* following a default or cascade at t_0, $\mathcal{L} = -\sum_i^B [C_{\mathrm{i}}(t_0) - C_{\mathrm{i}}(t_0 - 1)]$.

We simulate the above model with the parameters given in table 7.1, for 500 time steps. Results are averages over 10,000 identical simulations. Fit parameters to the following distribution functions are collected in table 7.2.

7.4.1.0.1 Time to first default We compute the distribution of the time to first default $\mathcal{T}_{\mathrm{fd}}$, for the normal and the transparent modes. Both distributions are practically Gaussian (kurtosis ~ 3.3, skewness ~ 0.4) with mean and standard deviation of $\mathcal{T}_{\mathrm{fd}}^{\mathrm{normal}} = 138.2 \pm 33.8$, and $\mathcal{T}_{\mathrm{fd}}^{\mathrm{transp.}} = 138.1 \pm 33.7$, respectively. This is expected, since typically the first default is triggered by a firm-default, which is (to first order) independent of the situation in the IB market, but only depends on the parameters describing the firms (μ_i, σ^{return}, C^{default}) and households (σ, ρ).

7.4.1.0.2 Losses In fig. 7.2(a) we show the distribution of losses to banks $\mathcal{L}$ for the the normal mode (red), where the selection of counterparties for IB loans is random and the transparent mode (blue), where banks sort their potential counterparties according to their inverse DebtRank, and then approach the least risky neighbor first for the IB loan. The fast mode is shown in green. The normal mode shows a heavy tail in the loss distribution, which completely disappears in the transparent and fast modes, where there

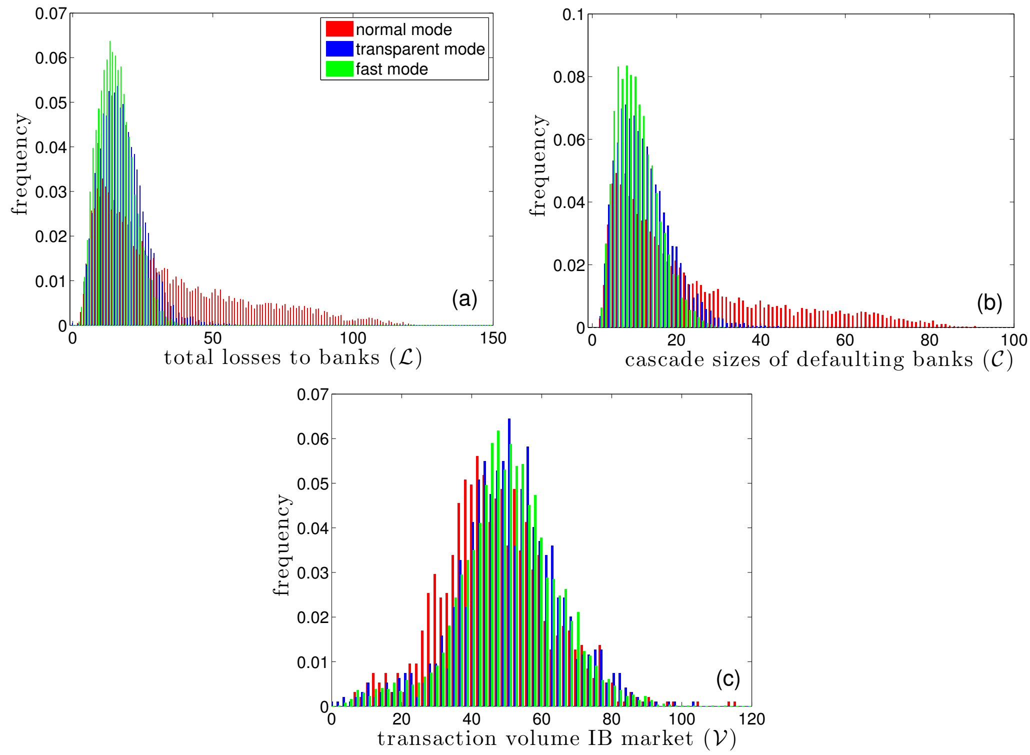


Figure 7.2: Comparison of the normal mode (red), i.e. random selection of counterparty for IB loans, with the transparent IB market (blue), where the order of counterparty selection is determined by the inverse DebtRank. The fast mode is shown in green. (a) Distribution of total losses to banks $\mathcal{L}$, (b) distribution of cascade sizes $\mathcal{C}$ of defaulting banks, and (c) distribution of transaction volume in the IB market $\mathcal{V}$. We performed 10,000 independent, identical simulations, each with 500 time steps, 100 banks, and the simulation parameters given in table 7.1. A is a fully connected graph.

are no losses higher than 50 and 40 units, respectively. Of course losses do not entirely disappear in the transparent scheme, since the credit risk that firms bring to the banking system can not be completely eliminated. The fast mode appears to be slightly safer than the transparent mode. Fits to all curves are found in table 7.2.

7.4.1.0.3 Cascade sizes The distribution of cascade-sizes $\mathcal{C}$ of defaulting banks is seen in fig. 7.2(b). Again the normal mode shows a heavy tail, meaning that in a non-negligible number of events, defaults of a single bank trigger a cascade of liquidity and equity problems through the system. In some cases up to 80 % of the banks collapse. In the transparent mode the likelihood for contagion is greatly reduced, and the maximum cascade size is limited by 40 banks in the transparent and about 30 in the fast mode.

7.4.2 Results for measures of efficiency for the system

To quantify the efficiency of the banking system we use the ratio of the sum of requested loans by the firms to the sum of loans actually payed out to firms, at a given time t, averaged over time,

$$E(t) = \frac{\sum_{i=1}^{B} l_i(t)}{\sum_{i=1}^{B} l_i^{\mathrm{req}}(t)}. \tag{7.21}$$

The efficiency of the system is then the time average $\mathcal{E} = \langle E(t) \rangle_t$, taken over the simulation. As another measure of efficiency we use the transaction volume in the IB market at a particular time $t = T$ in a typical simulation run,

$$\mathcal{V}(t) = \sum_{j=1}^{B} \sum_{i=1}^{B} l_{ji}(T) + l_{ji}(T - \tau). \tag{7.22}$$

The first term represents the new IB loans at time step T, the second the loans that are repaid. We set $T = 100$.

In fig. 7.2(c) we show the transaction volume in the IB market $\mathcal{V}$ of the three modes, normal (red), transparent (blue) and fast (green). The transparent and fast modes show a higher transaction volume indicating a more efficient IB market, where liquidity from banks with excess funds is more effectively channeled to those without. We verified that the ratio of requested to provided firm-loans, the efficiency $\mathcal{E}$, yields $\mathcal{E} \sim 1$, irrespective of the mode.

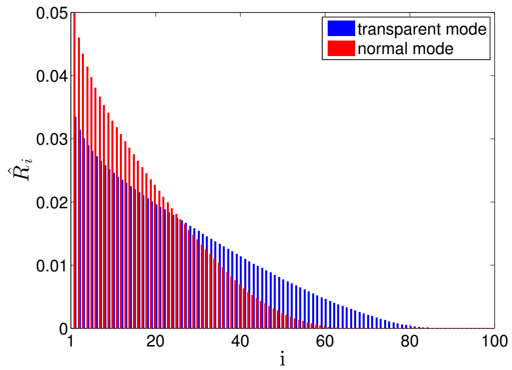


Figure 7.3: Normalized DebtRank, $\hat{R}_\mathrm{i}$ for individual banks in the normal (red) and the transparent mode (blue). Banks are ordered according to their DebtRank, the most risky is to the very left, the safest to the very right. The distribution is an average over 1000 simulation runs with an ER network, and shows the situation at time step $t = 100$.

7.4.3 Distribution functions of systemic risk

In fig. 7.3 we show the normalized DebtRank for all individual banks, for the normal (red), and the transparent scheme (blue). The normalized DebtRank is defined here as $\hat{R}_i = R_i / \sum_i R_i$. Banks are rank ordered according to their DebtRank so that the most risky bank is found to the very left, the safest to the very right. It is clear that the systemic risk impact in the transparent mode is spread more evenly throughout the system, whereas in the normal mode some banks appear to be much more dangerous to the system.

7.4.4 The emerging interbank network topology

In fig. 7.4 we show the effect of the bank selection process induced by the transparent mode on the IB liability network topology. The distributions of in-degrees k of the IB liability network $\mathrm{sgn}(L_{ij})$ for the normal (red) and transparent mode (blue) are shown at time step $t = 100$ for a totally connected bank-relation network, $A_{ij} = 1$ for all ij. The in-degree of $\mathrm{sgn}(L_{ij})$ for bank i is the total *number* of different banks that i has granted loans to within the last τ time steps. In the normal mode (random order of loan requests) the emerging liability network shows a Poisson distributed in-degree distribution (green), with $\lambda = 2.14$. The IB network topology of the normal node nicely coincides with the expected result from random linking. On average, half of the banks have excess liquidity and can provide loans to other banks. In the

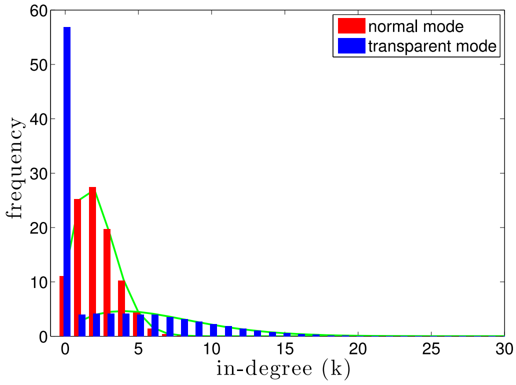


Figure 7.4: Distributions of in-degrees k of the IB liability network $\mathrm{sgn}(L_{ij})$ for the normal (red) and transparent mode (blue), for the case where the bank-relation network was fully connected ($A_{ij} = 1$ for all ij). The in-degree distribution (total number of different banks, a bank has granted loans to) is affected in the transparent mode because only banks with a low DebtRank provide loans to others. For the normal mode the distribution can be well fitted by a Poisson with $\lambda = 2.14$; the transparent mode is better fitted with a Weibull distribution with $a = 7.13$ and $b = 1.62$ (green lines). The distributions are an average over 1000 simulation runs and show the situation at time $t = 100$.

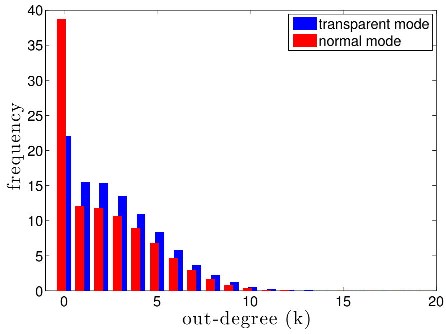


Figure 7.5: Distributions of out-degrees k of the IB liability network $\mathrm{sgn}(L_{ij})$ for the normal (red) and transparent mode (blue) at time $t = 100$. Same parameter settings as in the corresponding figure in the main text.

transparent mode only banks with a low DebtRank provide IB loans. This leads to fewer banks lending on the IB market and is reflected in fig. 7.4 by the high number of nodes with an in-degree of zero. The total demand for IB loans (which is approximately the same as in the normal mode) is now serviced by fewer banks with a low DebtRank. As a result, the in-degree distribution of the transparent mode broadens and is well fitted by a Weibull distribution with $a = 7.13$ and $b = 1.62$ (green). Regardless of the number of links, a bank with a low DebtRank, i.e. a bank that has borrowed little or nothing on the IB market, is not systemically risky. The out-degree distribution (total number of different banks a bank has received loans from) is mainly influenced by the cash needs of a bank. Therefore the out-degree distribution in the transparent mode is similar to the in-distribution in the normal mode, which is shown in fig. 7.5.

In fig. 7.5 the distributions of out-degrees k of the IB liability network $\mathrm{sgn}(L_{ij})$ for the normal (red) and transparent mode (blue) are shown. The simulation parameters are as in the main text. The out-degree distribution (total number of different banks a bank has received loans from) is mainly influenced by the cash needs of a bank. Therefore the out-degree distribution of the transparent mode is similar to the approximate random network distributions also seen in the in-degree of the normal mode. The different number of nodes with a degree of zero is a result of the slightly higher transaction volume in the transparent mode.

7.4.5 Comparison of random and scale-free interbank network topologies

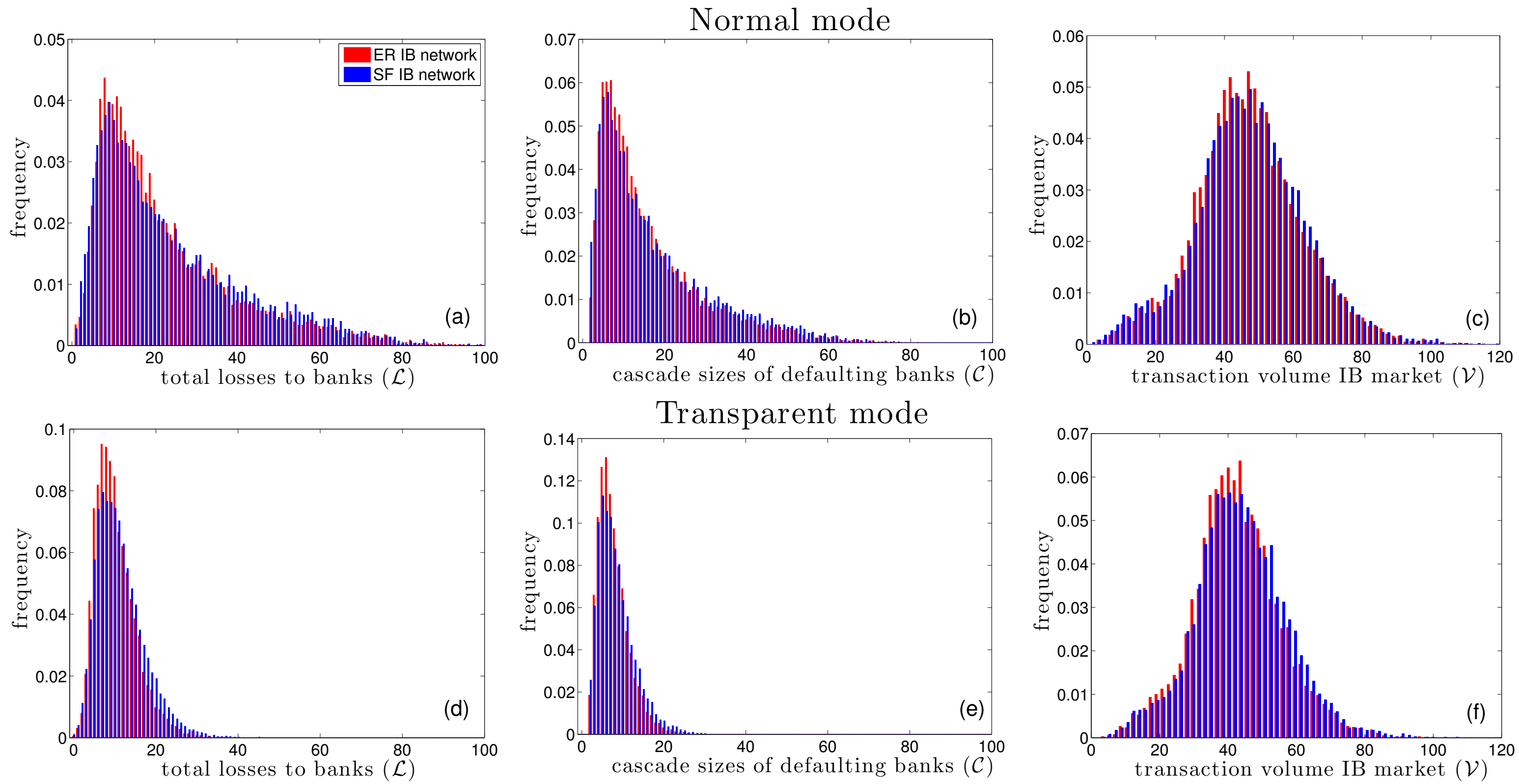


Figure 7.6: Distributions of the losses $\mathcal{L}$ for the normal mode (a) and the transparent mode (d), for an ER (red) and a SF network (blue), both with the same average connectivity $\langle k \rangle = 11.5$. Cascade sizes $\mathcal{C}$ for the normal mode are given in (b) and (e) for the transparent mode, the transaction volume in the IB market $\mathcal{V}$ is seen for the normal in (c), and the transparent mode in (f).

Figure 7.6 shows the risk measures for the normal and the transparent mode as computed with an Erdös-Rényi (ER) contact network (red) with $\gamma = 0.115$, and a scale-free (SF) network (produced with the Barabási-Albert algorithm). For the comparison of the SF and ER networks we chose an average connectivity of $\langle k \rangle = 11.5$. Again, we compare the normal mode, for which random selection of transaction partners among the neighbors in the IB network is performed (shown in top panels), with the transparent mode, where the selection of transaction partners in the IB networks follows the DebtRank matching (lower panels).

In fig. 7.6 we show the distribution of the losses to banks $\mathcal{L}$ in (a) and (d) for the normal and transparent mode respectively, the cascade sizes $\mathcal{C}$ in these modes are given in (b) and (e), and the transaction volume in the IB market $\mathcal{V}$ in (c) and (f). The results for the ER IB networks (red) are obtained with $\gamma = 0.115$ and the scale-free networks (blue) have the same average connectivity.

In both cases the SF IB network leads to a slightly less favorable situation in terms of losses and cascades. This is easily understandable in terms of vulnerability of SF networks, meaning that if a hub defaults it affects usually more banks than if a node in a random network defaults (with a degree much lower than a hub), see e.g. [186].

In the transaction volume an interesting effect occurs. For the transparent mode the volume decreases a little bit, see table 7.2. This is the case for the lower connectivity, $\langle k \rangle = 11.5$. In the main text (fully connected network) the volume increases in the transparent mode. The situation is made more clear in the next section where different connectivities are discussed.

7.4.6 Comparison of different connectivities of interbank networks

To compare the effect of connectivity in the IB networks we use a ER network with $\gamma = 1$ (fully connected – as in main text), $\gamma = 0.25$, and $\gamma = 0.115$. In fig. 7.7 we show the three measures, losses $\mathcal{L}$ in (a) for the normal mode and (d) for the transparent mode for the connectivities $\gamma = 1$ (red), $\gamma = 0.25$ (blue), and $\gamma = 0.115$ (green). The cascade sizes $\mathcal{C}$ in the same modes are given in (b) and (e), and the transaction volume in the IB market $\mathcal{V}$ in (c) and (f), respectively.

In both modes, higher connectivity means higher losses and larger cascades.

The transaction volume in the normal mode is almost insensitive to connectivity, but lowers in the transparent mode with decreasing connectivity. When comparing the transaction volumes for the normal and transparent modes we see that in the highly connected case the volume does not change. For the less connected cases, the transaction volume decreases a little in the transparent mode.

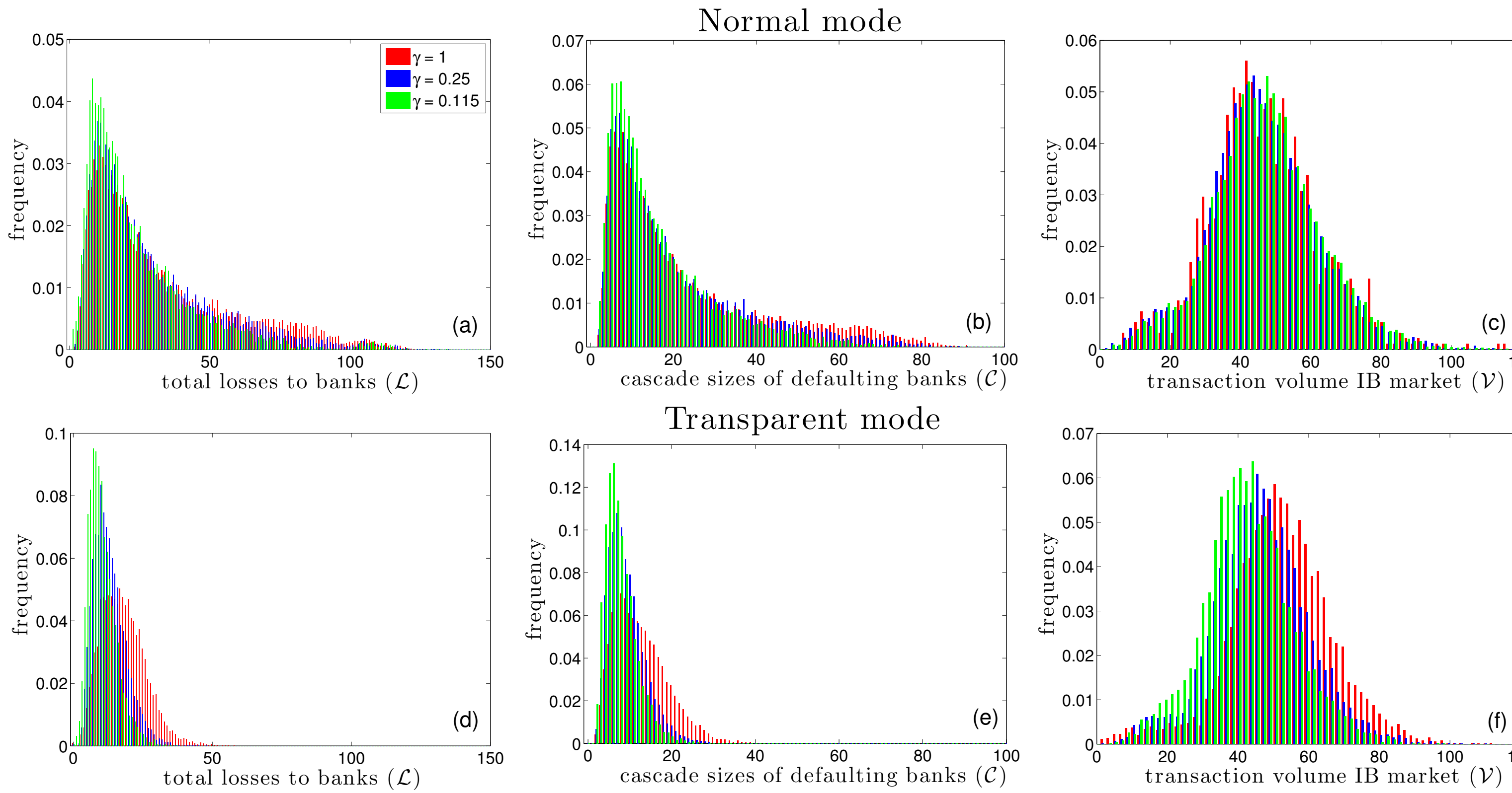


Figure 7.7: Distribution of losses $\mathcal{L}$ in the normal (a) and transparent mode (d), for a ER network with $\gamma = 1$ (red), $\gamma = 0.25$ (blue), and $\gamma = 0.115$ (green). The cascade sizes $\mathcal{C}$ for the normal mode are given in (b) and (e) for the transparent mode, the transaction volume $\mathcal{V}$ is seen for the normal in (c), and the transparent mode in (f).

7.4.7 Comparison of DebtRank and Katz rank

In fig. 7.8 we show the distribution functions of the three measures for (a) losses $\mathcal{L}$, (b) cascade sizes $\mathcal{C}$, and (c) transaction volume in the IB market $\mathcal{V}$, for the simulation performed with the DebtRank (red) algorithm and the Katz rank (blue). The performance of the two definitions is hardly distinguishable. It is clearly seen that in all measures there is practically no difference between the methods. Since the Katz rank is easier to implement this might practically favor the Katz rank, especially when it is intended to implement the fast mode.

7.4.8 Fits to distribution functions

The following fits to the curves have been attempted. The heavy tails in the losses and cascade size in the normal mode, are fitted by a power law. The exponents κ for the various cases are found in table 7.2. The loss and cascade curves in the transparent and fast mode were fitted (least squares) by $\exp[-a\log(x)^2 + b\log(x) - c]$. Values for a, b and c are in table 7.2. For the transaction volume we present the first four moments, mean, variance, skewness, and kurtosis also in table 7.2. Fit ranges were 10-70 (losses) and 10-50 (cascades) for the power laws, 2-35 (losses) and 2-25 (cascades) for the (approximate) log-exponentials.

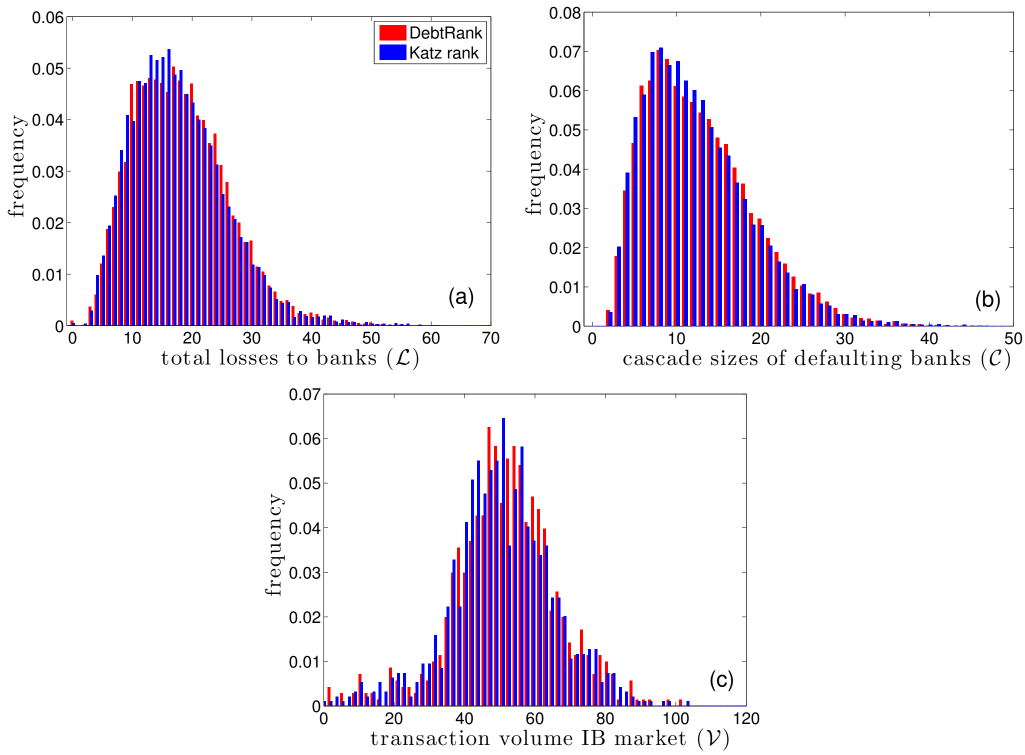


Figure 7.8: Comparison of the performance of the DebtRank (red) and the Katz rank (blue) for (a) Distributions of losses $\mathcal{L}$, (b) cascade sizes $\mathcal{C}$, and (c) transaction volume in the IB market $\mathcal{V}$. Both rank definitions provide practically identical results. Same simulation parameters as in previous figure.

Table 7.2: Fits to distribution functions

γ/m	NW	Mode	Losses (κ/a b c)			Cascades (κ/a b c)			Volume (mean std kurt skew)			
1	ER	normal	1.15			1.37			46.83	15.57	3.90	0.39
1	ER	transparent DR	1.60	8.08	13.20	1.38	5.86	8.88	51.88	15.05	4.91	0.04
1	ER	transparent KR	1.57	7.81	12.62	1.52	6.35	9.22	52.39	14.73	4.18	0.21
1	ER	fast KR	2.02	9.28	13.27	1.82	7.11	9.29	50.28	14.27	4.03	0.13
6	SF	normal	1.42			1.47			47.49	16.06	3.50	0.15
6	SF	transparent	1.81	7.07	9.19	1.74	5.87	7.06	43.63	13.50	3.60	0.22
0.25	ER	normal	1.27			1.39			46.57	15.43	3.57	0.24
0.115	ER	normal	1.66			1.75			47.25	15.46	3.55	0.26
0.25	ER	transparent	2.25	9.87	13.26	2.17	8.12	9.73	46.33	13.61	3.69	0.10
0.115	ER	transparent	2.30	8.85	10.60	2.24	7.57	8.33	42.55	12.77	3.49	0.21

7.5 Implications of increased transparency for economics and society

In this chapter we showed that the systemic risk, endogenously created in a financial network by the inability of banks to carry out correct risk-estimates of their counterparties, can be drastically reduced by introducing a minimum level of transparency. This becomes possible by introducing an incentive that makes borrowers more prone to borrow from systemically safe lenders. As a measure of the fraction of systemic risk of individual agents we use network centrality measures, such as the DebtRank and make it available to all nodes in the network at each point in time. We could show that the efficiency of the financial network with respect to the real economy is not affected by the proposed regulation mechanism. For this we verified that neither the volume of credit to firms (real economy) was reduced or lowered in the transparent scheme ($\mathcal{E} \sim 1$ in all modes), nor that the trading volume in the IB market was lower than in the normal mode. On the contrary, we could even find a slight increase in trading volume in the transparent mode. Maintaining of efficiency is possible since the regulation re-distributes risk in order to avoid the emergence of risky agents that might threaten the system, and does not reduce the trading volume in the real economy or in the IB liability network. Risky nodes that are low in DebtRank, are barred from the possibility of lending their excess reserves to others. This deprives them from making profits on IB loans, but also reduces their risk of being hit by defaulted credits. They only receive payments and do not issue more risk, meaning that over time they become less risky. Less risky banks are allowed to take more risk (lend more) and make more profits. The proposed mechanism makes the system safer in a self-organized critical manner. We explicitly show how this selection process re-shapes the IB network from a random graph in the normal mode to a fat tailed degree distribution in the transparent mode.

Note, that in our scheme the borrower determines who borrows from whom. Usually the lender is concerned if the borrower will be able to repay the loan. However, this credit default risk is not necessarily of systemic relevance. Lending to a bank with a large systemic risk can have relatively little consequences for the systemic importance of the lender, or the systemic risk of the system as a whole. In contrast, if a bank borrows from a systemically dangerous node the borrower inherits part of this risk, and increases the overall systemic risk. These facts are conveniently incorporated in the definition of the Debt- and Katz rank.

We found that the performance of the method is surprisingly insensitive to the choice of the particular centrality measure, or to the actual topology of the IB relation network (scale-free or random). Also the average connectivity $\bar{k}$ of the network is not relevant, as long as it remains in sensible regions ($\langle k \rangle \in [\sim 5, B]$). This suggests that the essence of the proposed scheme is that risk is spread more evenly across the network, which practically eliminates cascading failures.

A way to implement the proposed transparency in reality would be that central banks regularly compute the DebtRank of the asset-liability network (as reported or inferred from payment systems), and make it available to all banks. To enforce the regulation, the central bank could monitor IB loans through the payment system, and severely punish borrowers who failed to find less risky lenders. Note however, that the asset-liability network is only an approximation to the true risk network which is a multiplex network, meaning that the banks are linked by at least three risk-relevant networks: the asset-liability, the credit derivative and mutual collateral-holding networks. To derive practicable effective risk networks from the multiplex poses future technical challenges. A more market driven mechanism to obtain the same self-organized critical regulation dynamics is subject to further investigations. For future work it would be interesting to study the aspects of "controllability" introduced in [178] within the context of the presented transparency scheme. Currently, banks have no incentive whatsoever to disclose their systemic risk levels to others, and one could only force them to do so, or – formulated more positively – create appropriate incentives. This is maybe only possible with changes in the current jurisdiction.

Chapter 8

Controlling systemic risk in financial networks by means of a financial transaction tax

8.1 The problem of managing systemic risk: re-structuring financial networks

Failure to manage systemic risk (SR) has been proven to be extremely costly for society. The financial crisis of 2007-2008 and its consequences demonstrated the importance of reducing it. The threat of collapse of large parts of the financial system forced national governments to bailout hundreds of banks [187]. As a result, one observed falling global stock and real estate markets [188], a severe and global credit crunch [189], skyrocketing and prolonged unemployment rates, and several Western governments at the verge of bankruptcy. Bank bailouts caused dangerously high levels of sovereign debt around the world, and it has become necessary to find alternatives to finance bailouts [60]. The International Monetary Fund proposed a tax on banks, called the "financial stability contribution" (FSC), i.e. a contribution by the financial sector towards the public costs of the financial crisis, which is utilized to create reserves for future crises. Bank taxes have been proposed in many countries around the world, e.g. the "Financial Crisis Responsibility Fee" in the US. In several European countries, including Germany and Austria, bank taxes are currently in force. The European Commission proposed an EU-wide bank tax under the "Single Resolution Mechanism". In addition to bank taxes, a financial transactions tax (FTT) is being considered by many countries. A FTT is not a tax on financial institutions *per se* but a levy placed on specific types of financial transactions. Its main purpose, besides generating revenue for governments, is to curb the volatility of financial markets [190, 191]. Related empirical studies are generally inconclusive, and a causal relation between volatility and FTTs remains ambiguous [192, 193]. In response to the financial crisis of 2007-2008 a consensus for the need of new financial regulation emerged [99]. New financial regulations should be designed to mitigate the risk of the financial system as a whole. This approach to financial regulation is known as *macro prudential regulation*, and is currently being put in place around the globe [99, 101, 102]. The Basle III framework recognizes systemically important financial institutions (SIFI) and recommends increased capital requirements for them – the so called "SIFI surcharges" [54, 100]. Basle III further introduces the idea of *counter-cyclical buffers* that allows regulators to increase capital requirements during periods of high credit growth. No matter how well-intended these developments might be, they miss the central point about the nature of SR, and therefore may not be suitable to improve the stability of the financial system in a sustainable way. SR is tightly related to the *network structure* of financial assets and liabilities in a financial system. Management of SR is essentially a matter of re-structuring financial networks such that the probability of cascading failure is reduced, or ideally eliminated.

Credit risk is the risk that a borrower will default on a given debt by failing to make the full pre-specified repayments. It is usually seen as a risk that emerges between two counterparties once they have engaged in a financial transaction. The lender is the sole bearer of credit risk and accounts for the likelihood of failed repayments by demanding a risk premium. Lenders usually charge higher interest rates to borrowers that are more likely to default (risk-based pricing). Credit risk is relatively well understood, and can be mitigated through a of number methods and techniques [103]. The Basle accords provide an extensive framework, dealing foremost with the mitigation of credit risk [61, 62, 63]. When two counterparties are part of a financial system, for example as nodes in a financial network, the situation changes, and their transaction may affect the financial system as a whole. The lender is no more the sole bearer of credit risk, nor does credit risk depend on the financial conditions of the borrower alone. The impact of a default of the borrower is no longer limited to the lender, but may affect other creditors of the lender, which in turn may affect their creditors. Similarly, the lender is not only vulnerable to a default of the borrower but also to defaults of all debtors of that borrower, as well as their debtors. In financial networks credit risk is no longer limited to two counterparties, but becomes *systemic*.

SR is the risk that the financial system as a whole, or a large fraction of it, can no longer perform its function as a credit provider and collapses. In a narrow sense, SR is the notion of contagion or impact from the failure of a financial institution or group of institutions on the financial system and the wider economy [53, 54]. It is a result of the interconnected nature of financial transactions, and claims or liabilities in the financial system. It unfolds as secondary cascades of credit defaults, triggered by credit defaults between individual counterparties [23]. These cascades can potentially wipe out the financial system by a de-leveraging cascade [26, 27, 28, 29, 30, 31, 32, 2, 59, 80]. It is obvious that lenders have a strong incentive to mitigate credit risk. In the case of SR the situation is less clear as SR involves externalities, i.e. financial institutions manage their own risks but do *not* consider their impact on the system as a whole [104]. In fact, funding costs for large financial institutions are lowered due to a market expectation that the state will bailout banks, which are deemed to be systemically important [194]. Unless financial institutions are required to internalize costs of SR, institutions will have less incentive to minimize risks that are borne by the public [56]. Management of SR is, therefore, foremost in the public interest.

Several authors advocate for a taxation of SR [91, 56, 55, 84, 92, 105], while others are in favor of regulation due to the inherent difficulties of measuring SR [106]. SR is predominantly a network property of liability networks [98, 3]. Different financial network topologies will have different probabilities for systemic collapse, given the link density and the financial conditions of nodes are the same [42]. In this sense the management of SR becomes a technical problem of reshaping the topology of financial networks [21]. The goal is to do this in a way that does not reduce the credit provision capacity, or the transaction volume of the financial system. Data on the topology of credit networks is available to many Central Banks. Several studies on historical data show typical scale-free connectivity patterns in liability networks [33, 24, 34, 35, 36, 37, 131], including overnight markets [40], financial flows [38] and mutual cross holdings [41]. As a network property, SR can be (precisely) quantified by using network metrics [98, 3]. In particular, a relative network measure (DebtRank) can be assigned to all nodes in a financial network that specifies the fraction of SR they contribute to the system (institution- or node-specific SR) [3]. As shown later, it is natural to extend the notion of node-specific SR to individual liabilities between two counterparties (liability-specific SR) and to individual transactions (transaction-specific SR).

Recent econometric studies indicate that network measures could potentially serve as early warning indicators for crises [85, 86, 87]. In this context several econometric measures for SR have been proposed that focus (mainly) on statistics of losses, accompanied by a potential shortfall during periods of synchronized behavior where many institutions are simultaneously distressed [55, 56, 57, 58]. In particular, four measures have recently been proposed: conditional value-at-risk (CoVaR), systemic expected shortfall (SES), systemic risk indices (SRISK) and distressed insurance premium (DIP). CoVaR is defined as the value at risk (VaR) of the financial system, conditional on institutions being in distress. The contribution to SR of an institution is the difference between CoVaR, conditional on the institution being in distress, and CoVaR in its median state [55]. SES measures the propensity to be undercapitalized, given that the system as a whole is undercapitalized [56]. SES is related to leverage and the marginal expected shortfall (MES). SRISK is closely related to SES and as such a function of the size of an institution, its degree of leverage, and its MES [57]. DIP measures the price of insurance against systemic financial distress in the banking system and is closely related to the expected shortfall [58].

In this chapter we introduce a novel approach for the management of SR in financial networks. First, we develop a risk measure to quantify the marginal contribution of individual liabilities in financial networks to the overall SR. Second, we use this risk measure to design an incentive scheme where banks pay a Pigovian tax – the *systemic risk tax* (SRT) – on each transaction, which is proportional to the increase in overall SR that it would cause. Following this approach, financial institutions would internalize their externality, as they are "taxed" according to their marginal contribution to overall SR. This incentive scheme leads to a self-organized reduction of SR in the following way: Market participants looking for credit will try to avoid this tax by looking for credit opportunities that do not increase SR and are thus tax-free. As a result, the network rearranges toward a topology that, in combination with the financial conditions of individual institutions, will lead to a *de facto* elimination of SR. This is due to the fact that with the new topology cascading failures can no longer occur. With the help of an agent-based model (ABM), we show that financial institutions react to the SRT by rearranging the contract network over time such that overall SR is indeed drastically reduced. A number of ABMs have been used recently to study interactions between the financial system and the real economy, focusing on destabilizing feedback loops between the two sectors [195, 196, 197, 198]. We test the proposed SRT within the framework of the CRISIS macro-financial model[1]. In this ABM, we run the financial system in three modes. The first reflects the situation today, where banks do not care about their systemic impact and where interbank loans are traded with an "interbank offered rate". This interest rate only reflects the

[1] http://www.crisis-economics.eu

creditworthiness of the borrowing counterparty, and does not take SR into account. The second mode introduces the SRT. In this mode, the effective interest rate (interest rate + SRT) reflects both the creditworthiness of the borrowing counterparty and the SR increase associated with each transaction. For comparison, in a third mode we implement a financial transaction tax on *all* transactions (Tobin-like tax) that does not have any network re-structuring effect.

8.2 The systemic risk tax as a means for network re-structuring

The SRT is a levy placed on a financial transaction to offset the SR increase associated with that transaction. We show that SR associated with a transaction can be quantified by the DebtRank methodology, which was originally suggested as a recursive method to determine the systemic relevance of nodes within financial networks [98]. It is a quantity that measures the fraction of the total economic value (eq. (4.2)) in the network that is potentially affected by the default and distress of a node or a set of nodes, see section 4.1.2. For simplicity's sake let us think of the nodes in financial networks as banks. By $L_{ij}(t)$ we denote the liability (exposure[2]) network of a given financial system at a given moment. $L_{ij}(t) = \sum_k l_{ijk}(t)$ is the sum of all loans $l_{ijk}(t)$ that bank j currently extends to bank i. $C_i(t)$ is the capital of bank i at time t. If bank i defaults and cannot repay its loans, bank j loses the loans $L_{ij}(t)$. If j does not have enough capital available to cover the loss, j also defaults. Given $L_{ij}(t)$ and $C_i(t)$, the DebtRank $R_i(t) = R_i(L_{ij}(t), C_i(t))$ of node (bank) i can be computed, see eq. (4.6).

DebtRank has the precise meaning of economic loss (in Euros) that is caused by the distress or default of a node [98]. This precise meaning of the DebtRank allows us to define the *expected systemic loss* for the entire economy, which is the size of a possible loss times the probability of that loss occurring. For a single node i it is

$$EL_i^{\mathrm{syst}}(t) = P_i^{\mathrm{def}}(t)\, V(t)\, R_i(t) \quad , \tag{8.1}$$

with $P_i^{\mathrm{def}}(t)$ the probability of default of node i, and $V(t)$ the combined economic value of all nodes at time t. $R_i(t)$ measures the fraction of the total

[2] Note that the entries in $L_{ij}(t)$ are the liabilities bank i has towards bank j. We use the convention to write liabilities in the rows (second index) of L. If the matrix is read column-wise (transpose of L) we get the assets or loans banks hold with each other.

economic value (eq. (4.2)) that is potentially affected by node i. Assuming that we have B banks in the system, the total expected systemic loss is

$$EL^{\text{syst}}(t) = \sum_{i=1}^{B} EL_i^{\text{syst}}(t) = \sum_{i=1}^{B} P_i^{\text{def}}(t)\, V(t)\, R_i(t) \quad , \tag{8.2}$$

which has the precise meaning of the expected economic loss within a given timespan (Euros per year). In general, $P_i^{\text{def}}(t)$ is not known and can, in principle, also depend on the particular topology of various financial networks. Since R_i denotes the risk of financial contagion from the liability network $L_{ij}(t)$, the probability of default $P_i^{\text{def}}(t)$ should not explicitly depend on $L_{ij}(t)$. However, $P_i^{\text{def}}(t)$ can, in principle, depend on other networks, like the network of overlapping portfolios. Besides overlapping portfolios there are a number of reasons why default correlation exists, e.g. external events can trigger joint defaults of firms in the same geographic region or sector [199]. Note that we assume in eq. (8.2) that R_i denotes the risk of financial contagion and all other factors that lead to default correlations are comparably small (second order). Thus we calculate the total expected loss by summing the expected losses across banks. However, summing the expected losses across banks in general does not have the meaning of total expected loss because it ignores the joint probability of default. If the default correlation is known, additional terms containing the joint probability of default and the impact of a group can be added to eq. (8.2), see section 8.5.

To calculate the marginal contributions to the expected systemic loss, we start by defining the *net liability network* $L_{ij}^{\text{net}}(t) = \max[0, L_{ij}(t) - L_{ji}(t)]$. After we add a specific liability $L_{mn}(t)$, we denote the liability network by

$$L_{ij}^{(+mn)}(t) = L_{ij}^{\text{net}}(t) + \sum_{m,n} \delta_{im}\delta_{jn} L_{mn}(t) \quad , \tag{8.3}$$

where δ_{ij} is the Kronecker symbol. The marginal contribution of the specific liability $L_{mn}(t)$ on the expected systemic loss is

$$\Delta^{(+mn)} EL^{\text{syst}}(t) = \sum_{i=1}^{B} P_i^{\text{def}}(t) \left(V^{(+mn)}(t) R_i^{(+mn)}(t) - V(t) R_i(t) \right) \;, \tag{8.4}$$

where $R_i^{(+mn)}(t) = R_i(L_{ij}^{(+mn)}(t), C_i(t))$ is the DebtRank of the liability network and $V^{(+mn)}(t)$ the total economic value with the added liability $L_{mn}(t)$. Clearly, a positive $\Delta^{(+mn)} EL^{\text{syst}}(t)$ means that $L_{mn}(t)$ increases the total SR.

Finally, the marginal contribution of a single loan (or a transaction leading to that loan) can be calculated. We denote a loan of bank i to bank j by l_{ijk}.

The liability network changes to

$$L_{ij}^{(+k)}(t) = L_{ij}^{\mathrm{net}}(t) + \sum_{m,n,k} \delta_{im}\delta_{jn}\delta_{kk} l_{mnk}(t) \quad . \tag{8.5}$$

Since i and j can have a number of loans at a given time t, the index k numbers a specific loan between i and j. The marginal contribution of a single loan (transaction) $\Delta^{(+k)} EL^{\mathrm{syst}}(t)$ is obtained by substituting $L_{ij}^{(+mn)}(t)$ by $L_{ij}^{(+k)}(t)$ in eq. (8.4). In this way every existing loan in the financial system, as well as every hypothetical one, can be evaluated with respect to its marginal contribution to overall SR.

The central idea of the SRT is to tax every transaction between any two counterparties that increases SR in the system. The size of the tax is proportional to the increase of the expected systemic loss that this transaction adds to the system as seen at time t. The SRT for a transaction $l_{ijk}(t)$ between two banks i and j is given by

$$SRT_{ij}^{(+k)}(t) = \zeta \max \left[0, \sum_i P_i^{\mathrm{def}}(t) \left(V^{(+k)}(t) R_i^{(+k)}(t) - V(t) R_i(t) \right) \right] \quad . \tag{8.6}$$

Note that we assume in eq. (8.6) that defaults occur only on the maturity date of the loan. For simplicity's sake we do not discount. To allow defaults at any time, valuation can be done similarly to credit risk models as for example for credit default swaps [145, 146, 199][3].

ζ is a proportionality constant that specifies how much of the generated expected systemic loss is taxed. $\zeta = 1$ means that 100% of the expected systemic loss will be charged. $\zeta < 1$ means that only a fraction of the true SR increase is added on to the tax due from the institution responsible. ζ can be chosen such that the efficiency of the financial system is kept the same as it would be in the untaxed world. We show below that this is indeed possible.

[3] $SRT_{ij}^{(+k)}(t) = \zeta \max \left[0, \int_t^{t+T} d\tau\, v(\tau) \sum_i \hat{p}_i(\tau) \left(V^{(+k)}(t) R_i^{(+k)}(t) - V(t) R_i(t) \right) \right]$ Here $\hat{p}_i(\tau)$ is the default probability density of node i at time τ, and $v(\tau)$ the present value (at time t) of 1 Euro received at time τ. The default probability density is defined as $\hat{p}_i(t) = h(t) \exp^{-\int_0^{\tau} h(\tau) d\tau}$, where $h(t)$ is the hazard rate. The duration T of the loan is from t until $t + T$ and $R_i(t)$ is computed at time t.

8.3 Testing the systemic risk tax in the CRISIS macro-financial model

To test the economic and financial implications of the SRT we use the CRISIS macro-financial model. This is an economic simulator that combines a well-studied macroeconomic ABM [128, 129, 130] with an ABM of financial markets. We use a modified version of the model in [130] that includes an interbank market and is a *closed* economic system that allows no in- or out-flows of cash. For a comprehensive description of the model, see section 4.2.2, Delli Gatti et al. [130] and Gualdi et al. [14].

8.3.1 Interest rate formation in the CRISIS macro-financial model

There are B banks that offer firm loans at rates that take the individual specificity of banks (modeled by a uniformly distributed random variable) and the firms' creditworthiness into account. Firms pay a credit risk premium according to their creditworthiness that is modeled by a monotonically increasing function of their financial fragility. A firm's financial fragility is defined as the ratio between the outstanding debt and the liquid financial resources of the firm [130]. Specifically the interest rate for firm κ, borrowing from bank i is given by

$$r_i^\kappa(t) = \bar{r}(1 + \chi_i(t)\mu(l_\kappa(t)) \quad , \tag{8.7}$$

where $\bar{r}$ is a benchmark interest rate, $\chi_i(t)$ is the specificity of bank i – modeled as random variations in its operating costs, strategy, etc. and captured by a uniformly distributed random variable on the interval $(0, 1)$. $\mu(l_\kappa(t))$ is a proxy for the financial fragility of the borrower – modeled by a monotonically increasing function $\mu(\cdot)$ of the borrower's debt to liquidity ratio $l_\kappa(t)$. The hyperbolic tangent is chosen for $\mu(\cdot)$.

Banks try to provide firm loans and grant them if they have enough liquidity. If they do not have enough cash, they approach other banks in the interbank market to obtain the required amount. If a bank does not have enough cash, and cannot raise the full amount for the requested firm loan on the interbank market, it does not pay out the loan. Interbank and firm loans have the same duration. Additional refinancing costs of banks remain with the firms. Each time step firms and banks repay τ percent of their outstanding debt. If banks have excess liquidity they offer it on the interbank market. The interbank market is modeled after an electronic marketplace where, in principle, all participants can enter into business relationships. In the model, banks choose the interbank offer with the most favorable rate. This does not mean that the emerging interbank network is fully connected. Emerging interbank networks are shown in fig. 8.1 and (weighted) degree distributions can be found in fig. 8.6. Interbank rates $r_{ij}(t)$ offered by bank i to bank j take into account the specificity of bank i and the creditworthiness of bank j. Specifically the interest rate on the interbank market for bank j borrowing from bank i is given by

$$r_{ij}(t) = \bar{r}(1 + \psi_i(t)\mu(l_j(t)) \quad , \tag{8.8}$$

where $\bar{r}$ is a benchmark interest rate, $\psi_i(t)$ is the specificity of bank i, modeled as random variations in its operating costs, strategy, etc. and captured by a uniformly distributed random variable on the interval $(0, 0.1)$. $\mu(l_j(t))$ is a proxy for the financial fragility of the borrower, modeled by a monotonically increasing function $\mu(\cdot)$ of the borrower's leverage $l_j(t)$. As the monotonically increasing function again the hyperbolic tangent is chosen. Banks add the additional refinancing costs to the offered interest rate for firms. Therefore the interest rate for firm κ, borrowing from bank i, which requires additional liquidity from bank j is given by

$$r^{\kappa}_{ij}(t) = r^{\kappa}_{i}(t) + \frac{l_{jik}(t)}{b_\kappa(t)} r_{ji}(t) = \bar{r}\left(1 + \chi_i(t)\mu(l_\kappa(t)) + \frac{l_{jik}(t)}{b_\kappa(t)}\psi_j(t)\mu(l_i(t))\right) \quad , \tag{8.9}$$

where $b_\kappa(t)$ is the firm loan and $l_{jik}(t)/b_\kappa(t)$ is the ratio between the interbank and the firm loan.

8.3.2 Implementation of the systemic risk tax and the "Tobin tax"

A systemic risk premium, in form of the SRT, is imposed on all interbank transactions. Before entering a desired loan $l_{ijk}(t)$, the credit seeking banks i can get quotes for the $SRT^{(+k)}_{ij}(t)$ rates from the Central Bank, for various banks j. They choose the interbank offer from bank j with the smallest total rate, which is composed of $r^{\text{total}}_{ij}(t) = r_{ij}(t) + SRT^{(+k)}_{ij}(t)$. All other transactions are exempted from the SRT. In contrast to current market practice, the effective interest rate reflects both the creditworthiness of the borrowing counterparty and the SR increase associated with each transaction. The SRT is collected in a bailout fund. The SRT from the main text is given by

$$SRT_{ij}^{(+k)}(t) = \zeta \max\left[0, \sum_i P_i^{\mathrm{def}}(t)\left(V^{(+k)}(t)R_i^{(+k)}(t) - V(t)R_i(t)\right)\right] \quad . \tag{8.10}$$

For $P_i^{\mathrm{def}}(t)$ we use a proxy for the financial fragility of the borrower, modeled by a monotonically increasing function $P_i^{\mathrm{def}}(t) = 0.01\mu(l_i(t))$ of the borrower's leverage $l_i(t)$ at time t.

For comparison we implement a Tobin-like tax ()[190]) financial transaction tax (FFT) for interbank loans. We impose a constant tax rate of 0.2% of the transaction (this is about 5% of the interbank interest rates) on all interbank rates on offer. Other transactions are not taxed. The FTT makes lending less attractive for firms that borrow from banks needing liquidity from the interbank market, as refinancing costs remain with the firms.

Interbank rates $r_{ij}(t)$ offered by bank i to bank j including the FFT or the SRT are composed of

$$r_{ij}^{\mathrm{total}}(t) = r_{ij}(t) + TAX \quad . \tag{8.11}$$

In case of the FFT the tax term is simply a constant tax rate of 0.2%

$$r_{ij}^{\mathrm{total}}(t) = r_{ij}(t) + 0.002 \quad . \tag{8.12}$$

To obtain a tax rate, the SRT must be expressed as a ratio with respect to the interbank loan ($SRT_{ij}^{(+k)}(t)/l_{jik}(t)$). The total rate is then given by

$$r_{ij}^{\mathrm{total}}(t) = r_{ij}(t) + \frac{SRT_{ij}^{(+k)}(t)}{l_{ijk}(t)} \quad , \tag{8.13}$$

where $r_{ij}(t)$ is from eq. (8.8). Banks add the additional refinancing costs, including taxes, to the offered interest rate for firms. Therefore eq. (8.7) becomes for the Tobin-like tax

$$r_{ij}^{\kappa}(t) = r_i^{\kappa}(t) + \frac{l_{jik}(t)}{b_\kappa(t)} r_{ji}^{\mathrm{total}}(t) = \bar{r}\left(1 + \chi_i(t)\mu(l_\kappa(t)) + \frac{l_{jik}(t)}{b_\kappa(t)}\psi_j(t)\mu(l_i(t))\right) + \frac{l_{jik}(t)}{b_\kappa(t)} 0.002 \quad , \tag{8.14}$$

and in case of the SRT,

$$r_{ij}^{\kappa}(t) = r_i^{\kappa}(t) + \frac{l_{jik}(t)}{b_\kappa(t)} r_{ji}^{\mathrm{total}}(t) = \bar{r}\left(1 + \chi_i(t)\mu(l_\kappa(t)) + \frac{l_{jik}(t)}{b_\kappa(t)}\psi_j(t)\mu(l_i(t))\right) + \frac{SRT_{ji}^{(+k)}(t)}{b_\kappa(t)} \quad . \tag{8.15}$$

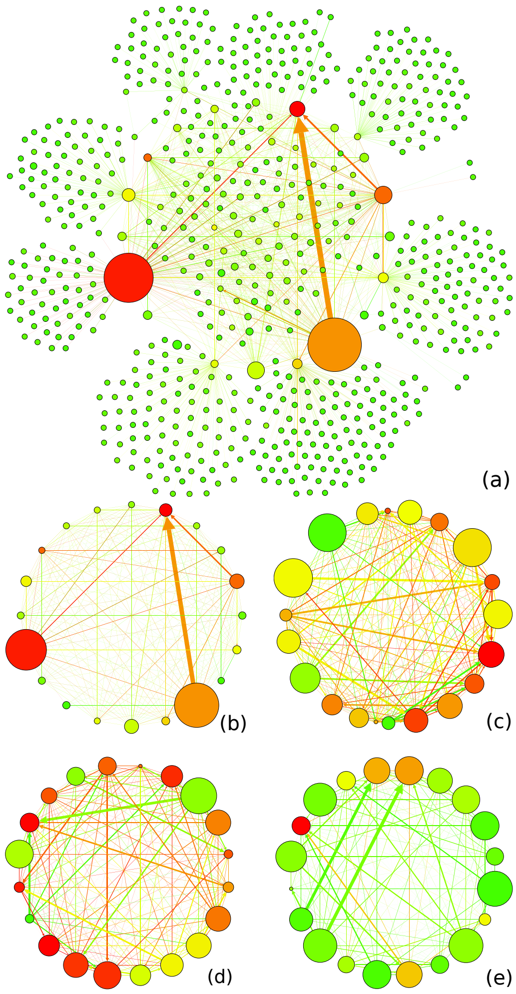


Figure 8.1: Banking network. (a) Austrian interbank network at the end of the first quarter of 2006, (b) the 20 largest banks of the Austrian interbank network only, (c) banking network of the ABM without a tax, (d) with the FTT, and (e) with the SRT. Nodes (banks) are colored according to their systemic impact R_i, from systemically important banks (red) to unimportant (green). The node size represents the capitalization of the banks. Width of the links are the exposures of the banks in the interbank network and the color is according to the source.

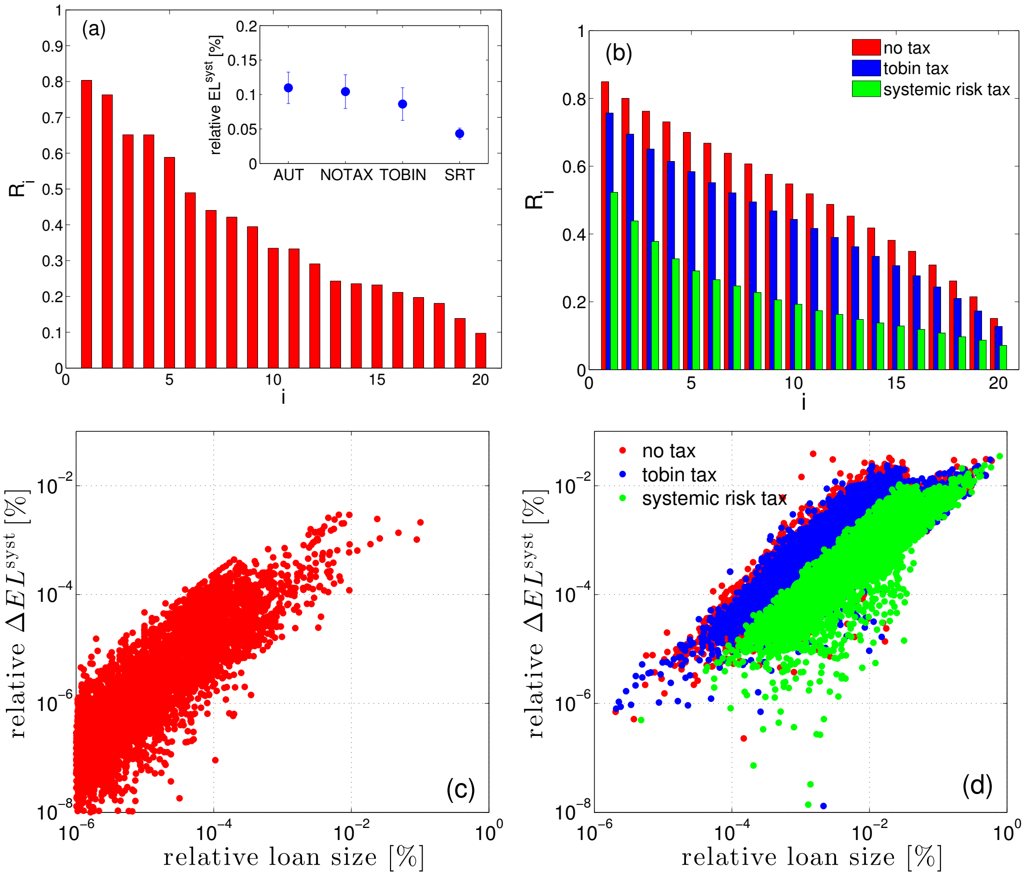


Figure 8.2: Expected systemic loss as measured by DebtRank, $EL_i^{\rm syst} \propto R_i$. (a) DebtRank, R_i of the 20 largest banks of the Austrian banking sector at the end of the first quarter of 2006. Banks are ordered by DebtRank, the most important being to the very left. Inset: Expected systemic loss from all banks for the Austrian interbank data and the three model modes. Here the SR measure is the size of a potential loss for the entire economy times the probability of that loss occurring as defined in eq. (8.4). (b) Model results for R_i: without a tax (red), with the FTT (blue), and with the SRT (green). Clearly, the SRT drastically reduces the SR contributions of individual banks. The situation without tax resembles the empirical distribution. (c) Marginal contributions on expected systemic loss $\Delta^{(+mn)} EL^{\rm syst}$ of individual interbank liabilities L_{mn} vs. the relative size of interbank loans in double logarithmic scale. Every data point represents an interbank liability $L_{mn}^{\rm data}$, see section 8.4.1. The loan size captures the credit risk for lenders, whereas $\Delta^{(+mn)} EL^{\rm syst}$ is the SR of the liability. (d) Marginal contributions for the simulations in the three modes. The SRT reduces SR but leaves contract sizes unchanged.

Table 8.1: List of the parameters as used in the model.

number of banks	$B = 20$
number of firms/capitalists	$F = 100$
number of workers (households)	$H = 1300$
share of dividends	$div = 0.2$
general refinancing rate	$\bar{r} = 0.02$
labour productivity	$\alpha = 0.1$
credit demand contraction	$\phi = 0.8$
rate of debt reimbursement	$\tau = 0.05$
wage rate	$wb = 1$
number of applications in consumption goods market	$z = 2$
propensity to consume	$c = 0.8$
number of applications in credit market	$n = 5$

8.3.3 The parameters of the model

All parameters of the model are collected in table 8.1.

8.4 Containing systemic risk: impact of the systemic risk tax on global systemic risk

We implement the above model in Matlab code for $B = 20$ banks, $F = 100$ firms, and $H = 1300$ households. The model is run in three modes, without any tax, with the SRT, and with a Tobin-like financial transaction tax. Results are averages over $10,000$ independent, identical simulations across 500 time steps. We set $\zeta = 0.02$ (see section 8.2), and for the Tobin-like financial transaction tax we impose a constant tax rate of 0.2% of the transaction. For different tax rates for the Tobin-like financial transaction tax and an alternative mode in which the SRT is set to the true increase in SR associated with each transaction ($\zeta = 1$), see section 8.4.3.

8.4.1 Comparison of model results with historical data

We compare model results to historical, anonymized, and linearly transformed interbank liability data provided by the Austrian Central Bank (OeNB). Data provided by the Austrian Central Bank contains fully anonymized, and linearly transformed interbank liabilities/exposures $L_{ij}^{\text{data}}(t)$ from the entire Austrian banking system, comprised of about 800 banks over 12 consecutive quarters from 2006-2008. The data set additionally includes total assets, total liabilities, assets due from banks, liabilities due to banks, and liquid assets (without interbank assets/liabilities) for all banks again in anonymized form (see section 4.3.1). The data does not contain credit ratings of banks. Therefore we assume $P_i^{\mathrm{def}} = 0.0025$ for all banks in the dataset. This corresponds approximately to Standard & Poor's One-Year Global Corporate Default Rates for Rating Categories A+, A, and BBB+ in 2008 [200]. Representative Austrian banks are in the Rating Categories A+, A and A-. In fig. 8.1(a) we show a snapshot of the Austrian interbank network at the end of the first quarter of 2006. Nodes symbolize the banks of the Austrian banking system and links represent their lending relations (weighted by the exposure). Nodes are colored according to their systemic impact R_i, from systemically important banks (red) to unimportant (green). The node size represents the capitalization of banks and the width of the links symbolizes the exposures. In fig. 8.1(b) we show only the 20 largest banks of the Austrian interbank network. Clearly, the 20 largest banks contribute most to overall SR (red and orange dots). Figure 8.1(c) shows results from the ABM without a tax, (d) with the FTT, and (e) with the SRT. The SRT effectively reduces the spreading of SR by preventing systemically important nodes from lending. This can be seen from the fact that there are only green links in fig. 8.1(e). In the snapshot of the Austrian interbank network and in the model without the SRT numerous red links are clearly visible. In fig. 8.2(a) we show SR as measured by DebtRank R_i. In particular, we show R_i for the 20 largest banks (according to total assets) of the Austrian banking sector at the end of the first quarter of 2006. Here we calculate R_i from $L_{ij}^{\mathrm{data}}(t)$ (see section 8.4.1), in fig. 8.2(b) we use the net liability network $L_{ij}^{\mathrm{net}}(t)$. Banks are ordered by their DebtRank, the systemically most important is to the very left, the least important to the very right. The ABM results for $R_i(t)$ are presented in fig. 8.2(b): without a tax (red), with the FTT (blue) and with the SRT (green). The shown distributions are averages over $10,000$ independent simulations. Clearly, the SRT drastically reduces the SR contributions of individual banks. The situation without tax resembles the empirical distribution remarkably well. In fig. 8.2(c) the marginal contributions on expected systemic loss from eq. (8.4) are presented for all individual interbank liabilities L_{mn}^{data}, as a function of the relative size of interbank loans. Every data point represents a single interbank liability L_{mn}^{data} from bank m to n. Interbank loans are themselves power-law distributed (not shown), which is known empirically [34]. The loan size captures the credit risk for lenders, whereas $\Delta^{(+mn)}EL^{\mathrm{syst}}$ is the SR contribution of the liability. Figure 8.2(d) shows the marginal contributions for the ABM simulations for the three modes. It is clearly visible that the

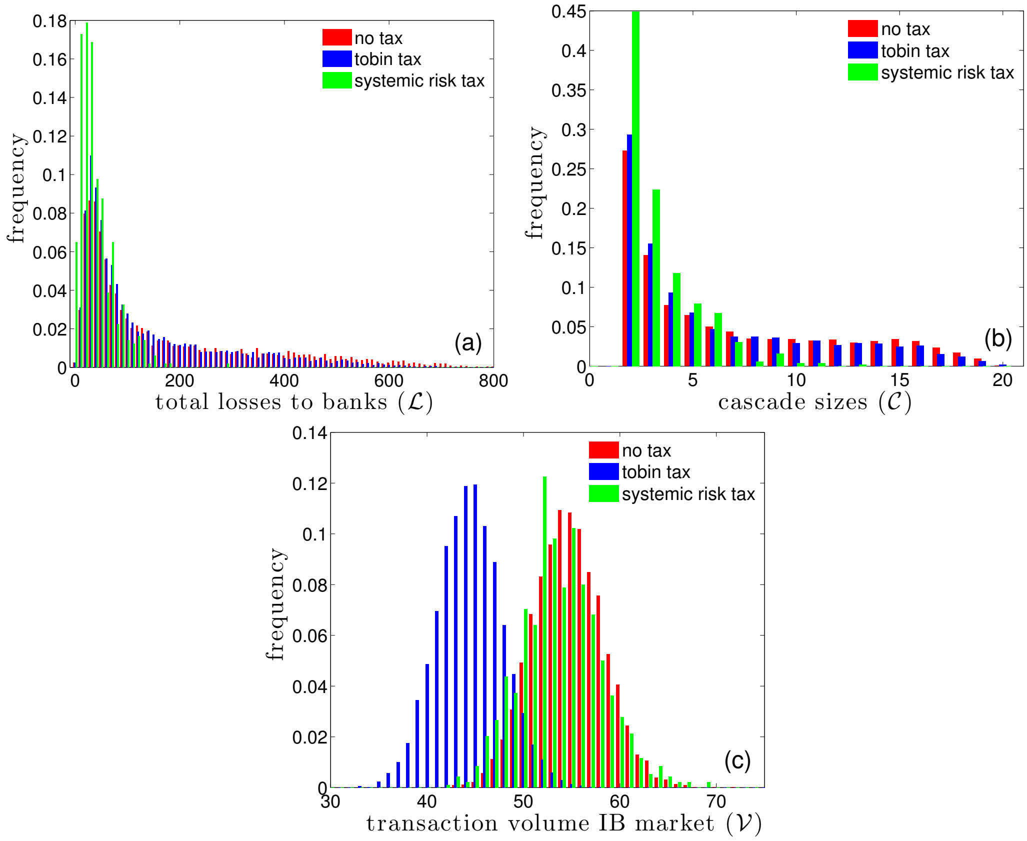


Figure 8.3: Comparison of no transaction tax (red) on interbank loans, with systemic risk tax (green), and Tobin tax (blue). (a) Distribution of total losses to banks $\mathcal{L}$, (b) distribution of cascade sizes $\mathcal{C}$ of defaulting banks, and (c) distribution of total transaction volume in the interbank market $\mathcal{V}$. 10,000 independent, identical simulations, each with 500 time steps, 20 banks.

SRT reduces the SR contribution of liabilities by approximately an order of magnitude (note the log scale), but leaves contract sizes practically unchanged.

8.4.2 Performance and efficiency indicators of the agents

We use the following three observables: (1) the size of the cascade, $\mathcal{C}$ as the number of defaulting banks triggered by an initial bank default ($1 \le \mathcal{C} \le B$), (2) the total losses to banks following a default or cascade of defaults, $\mathcal{L} = \sum_{i \in I} \sum_{j=1}^{B} L_{ij}(t)$, where I is the set of defaulting banks, and (3) the average transaction volume in the interbank market in simulation runs longer than

100 time steps,

$$\mathcal{V} = \frac{1}{T} \sum_{t=1}^{T} \sum_{j=1}^{B} \sum_{i=1}^{B} \sum_{k \in K} l_{jik}(t) \quad , \tag{8.16}$$

where K represents new interbank loans at time step t. The effects of the SRT and the FTT on total losses to banks $\mathcal{L}$ that occur as a consequence of bank defaults are shown in fig. 8.3(a). Clearly, the mode without tax (red) produces fat tails in the loss distributions of the banking sector. The Tobin tax slightly reduces losses (almost not visible). The SRT gets completely rid of big losses in the system (green). The remaining losses are from firm defaults, which represents the economic risk in the system. Note that economic risk can hardly be managed. This elimination of losses on the interbank market is due to the fact that under the SRT the possibility for cascading defaults is drastically reduced. This is seen in fig. 8.3(b), where the distributions of cascade sizes $\mathcal{S}$ for the three modes are compared. While the untaxed mode produces considerable cascade sizes of up to 20 banks, the maximum cascade sizes under the SRT is less than half. The Tobin tax more or less follows the untaxed case. As mentioned above, the interbank loan sizes are practically unchanged under the SRT. This is also true for the total transaction volume $\mathcal{V}$ in the interbank market, as can be seen in fig. 8.3(c), where the distributions of transaction volumes at time step 100 are shown. Obviously, the situation for the SRT (green) is very similar to the untaxed case (red), whereas the transaction volume is drastically reduced in the FTT scenario (blue), as expected.

8.4.3 Comparison of different tax rates for the Tobin-like financial transaction tax

In fig. 8.4 we show the distribution functions of the three measures for (a) losses $\mathcal{L}$, (b) cascade sizes $\mathcal{C}$, (c) transaction volume in the interbank market $\mathcal{V}$ and (d) the distribution of DebtRank R_i, for the simulations performed with different tax rates for the Tobin-like financial transaction tax, 0.1% (red), 0.2% (blue) and 0.5% (green). Clearly, the shape of the distribution of losses $\mathcal{L}$ and cascade sizes $\mathcal{C}$ are similar. The tail of the distributions is only reduced due to a decrease in efficiency (credit volume), as can be seen in fig. 8.4(c). Evidently, average losses $\mathcal{L}$ are reduced at the cost of a loss of efficiency by roughly the same factor.

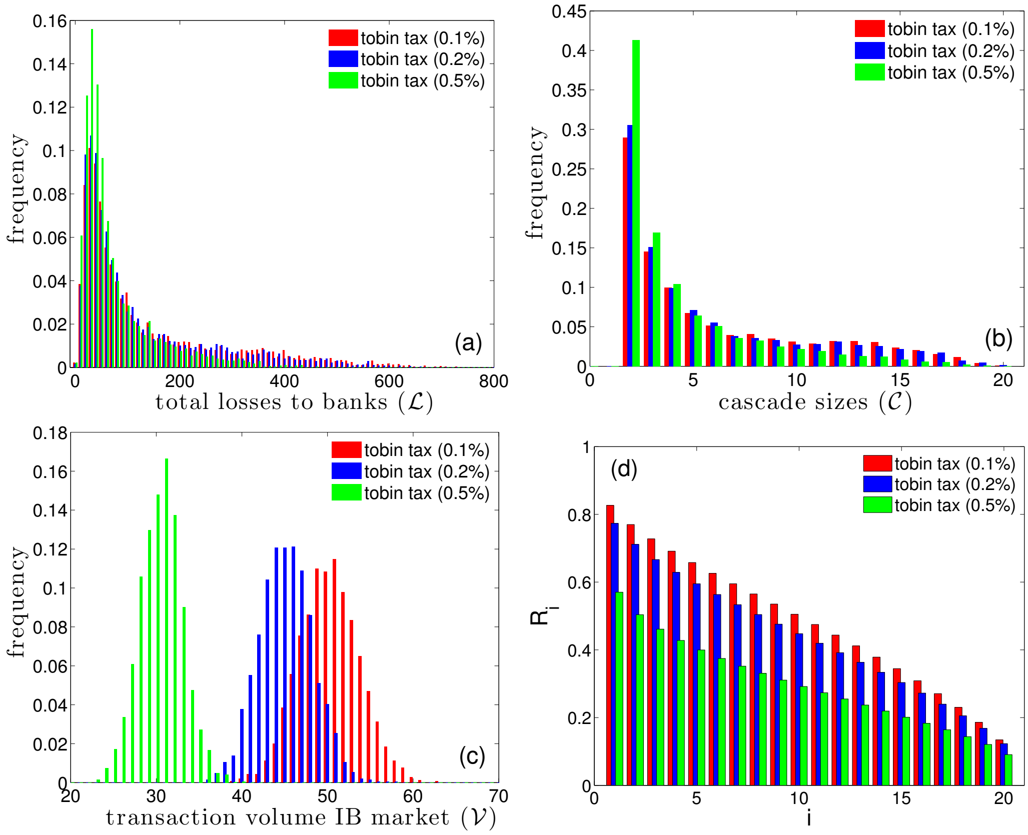


Figure 8.4: Comparison of different tax rates for the Tobin-like financial transaction tax, 0.1% (red), 0.2% (blue) and 0.5% (green). (a) Distribution of total losses to banks $\mathcal{L}$, (b) distribution of cascade sizes $\mathcal{C}$ of defaulting banks and (c) distribution of total transaction volume in the interbank market $\mathcal{V}$, (d) distribution of DebtRank R_i. Banks are ordered by DebtRank, the most important being to the very left. 10,000 independent, identical simulations, each with 500 time steps, 20 banks.

8.4.4 Comparison of different systemic risk tax levels

For the comparison of different levels of the SRT we choose $\zeta = 0.02$ (red) and $\zeta = 1$ (blue), as shown in fig. 8.5. Again, we compare the three measures for (a) losses $\mathcal{L}$, (b) cascade sizes $\mathcal{C}$, (c) transaction volume in the interbank market $\mathcal{V}$ and (d) the distribution of DebtRank R_i. Clearly, for both ζ the SRT gets completely rid of big losses in the system. $\zeta = 1$ reduces average losses $\mathcal{L}$ by a factor of 2 compared to the case of $\zeta = 0.02$, at the cost of a loss of efficiency by roughly the same factor, as can be seen in fig. 8.5(c). The SRT with ($\zeta = 1$) leads to homogeneous SR spreading across all agents, as shown in fig. 8.5(d).

8.4.5 The emerging interbank network topology

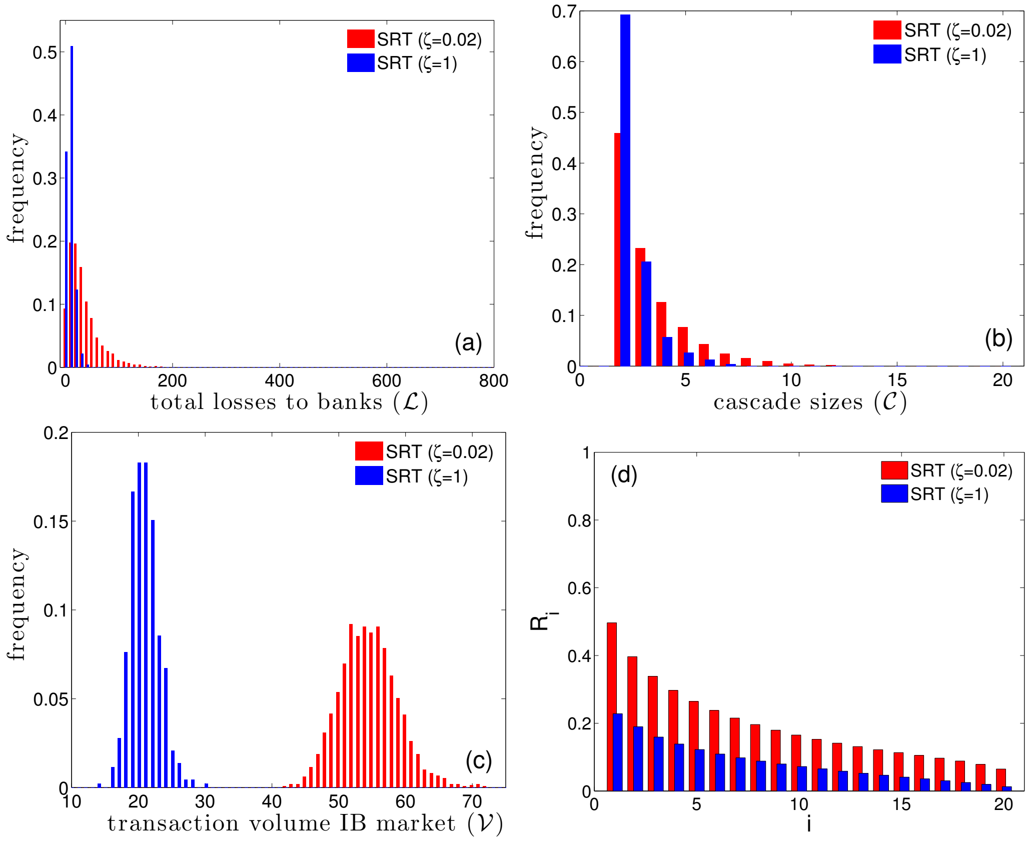


Figure 8.5: Comparison of different levels of the SRT, $\zeta = 0.02$ (red) and $\zeta = 1$ (blue). (a) Distribution of total losses to banks $\mathcal{L}$, (b) distribution of cascade sizes $\mathcal{C}$ of defaulting banks and (c) distribution of total transaction volume in the interbank market $\mathcal{V}$, (d) distribution of DebtRank R_i. Banks are ordered by DebtRank, the most important being to the very left. $10,000$ independent, identical simulations, each with 500 time steps, 20 banks.

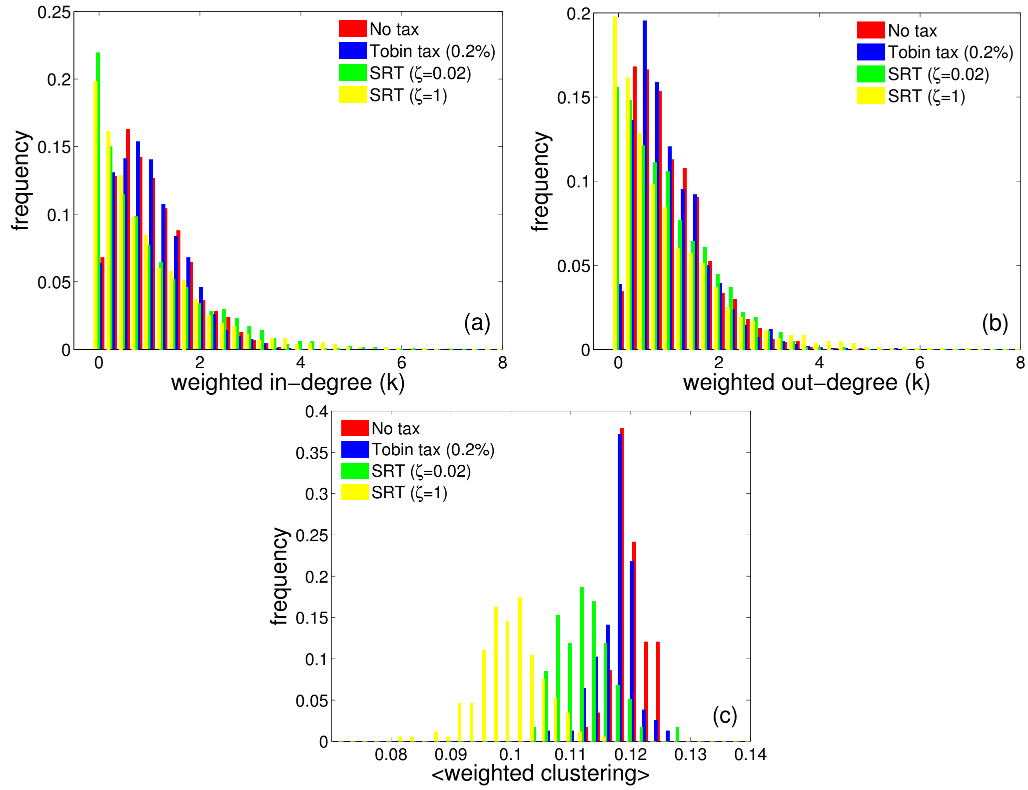


Figure 8.6: The effect of the bank selection process induced by the SRT on the interbank liability network topology. Distributions of weighted in-degrees k (a), and weighted out-degrees k (b) of the interbank liability network $(L_{ij}^{\mathrm{net}}(t))$, without transaction tax (red), 0.2% Tobin tax (blue), the SRT $(\zeta = 0.02)$ (green) and the SRT $(\zeta = 1)$ (yellow). (c) Shows the average weighted clustering coefficient of the interbank liability network $(L_{ij}^{\mathrm{net}}(t))$ from the model. The weighted in-degrees distributions are clearly affected in the SRT modes. The weighted out-degree distribution is mainly influenced by the cash needs of a bank. Therefore, the weighted out-degree distribution of the SRT modes is less clearly affected. The distributions are from an average over 1000 simulations runs and show the situation at time $t = 100$.

Table 8.2: Network measures

Mode	$< k >$	$< k^{weighted} >$	$< C_i >$	$< C_i^{weighted} >$	$< g_i >$	$< g_i^{weighted} >$
Normal	9.43(5)	38.4(35)	0.136(5)	0.119(3)	10.3(7)	40.2(53)
Tobin tax	9.39(9)	32.4(32)	0.135(5)	0.117(3)	10.4(7)	40.0(55)
SRT ($\zeta = 0.02$)	9.15(13)	25.4(35)	0.138(6)	0.112(5)	11.9(20)	44.1(76)
SRT ($\zeta = 1$)	8.73(20)	7.4(14)	0.122(6)	0.100(4)	11.3(12)	45.9(68)

In fig. 8.6 we show the effect of the bank selection process induced by the SRT on the interbank liability network topology. The distributions of weighted in-degrees k of the interbank liability network ($L_{ij}^{\mathrm{net}}(t)$), without transaction tax (red), 0.2% Tobin tax (blue), the SRT ($\zeta = 0.02$) (green) and, the SRT ($\zeta = 1$) (yellow) are shown in fig. 8.6(a). Without transaction tax, the emerging liability network shows Poisson distributed in-degrees. The interbank network topology without transaction tax coincides nicely with the expected result from random linking. In the SRT modes, market participants looking for credit will try to avoid the tax by looking for credit opportunities that do not increase SR and are thus tax-free. This leads to fewer banks lending on the interbank market and is reflected in fig. 8.6(a) by the high number of nodes with a low weighted in-degree.

The total demand for interbank loans (which is approximately the same for the SRT with $\zeta = 0.02$ as without transaction tax) is now serviced by fewer banks. As a result, the in-degree distribution of the SRT mode broadens and has a fat tail. The out-degree distribution is mainly influenced by the cash needs of a bank. Therefore, the weighted out-degree distribution of the SRT modes is less clearly affected, which is shown in fig. 8.6(b).

In fig. 8.6(c) we show the average weighted clustering coefficient of the interbank liability network ($L_{ij}^{\mathrm{net}}(t)$), without transaction tax (red), 0.2% Tobin tax (blue), the SRT ($\zeta = 0.02$) (green) and the SRT ($\zeta = 1$) (yellow). Average weighted clustering coefficients are calculated according to Barrat et al. [201]. The average clustering is roughly the same without a transaction tax on interbank loans and for the 0.2% Tobin tax. The SRT reduces average clustering, as can be seen in fig. 8.6(c).

Mean values of various centrality measures, averaged over 1000 simulations runs, can be found in table 8.2. $\langle k \rangle$ and $\langle k^{weighted} \rangle$ shows the mean degree and the weighted mean degree for the different modes. $\langle k \rangle$ is approximately the same for all modes. $\langle k^{weighted} \rangle$ shows the largest value for the normal mode and lower values in all other modes. Clearly, with the SRT ($\zeta = 1$) $\langle k^{weighted} \rangle$ is substantially reduced. With $\langle C_i \rangle$ and $\langle C_i^{weighted} \rangle$ we show values for the average clustering coefficients and the average weighted clustering coefficients from fig. 8.6(c). Additionally, we provide values for the average betweenness centrality ($\langle g_i \rangle$) and the average weighted betweenness centrality ($\langle g_i^{weighted} \rangle$) for the different modes. The SRT increases both the $\langle g_i \rangle$ and the $\langle g_i^{weighted} \rangle$.

8.5 Implications of the systemic risk tax for economics and society

In this chapter we extend the notion of SR to individual liabilities within a financial network. We show with empirical data of nation-wide interbank liabilities that this is indeed feasible. The notion of liability-specific SR allows us to quantify the marginal contribution of every financial transaction to overall SR. We propose a Pigovian tax (SRT) on every SR-increasing transaction, proportional to the marginal contribution to overall SR. By trying to avoid the SRT, financial institutions effectively rearrange the contract network over time, such that cascading failures can no longer occur. This process leads to a self-organized reduction of SR.

The notion of liability-specific SR is based on the probability of default and the impact of a failure of a financial institution, as measured by DebtRank. A central idea of this chapter is to separate *default risk* from *contagion risk*. Contagion risk is the risk that a default by one institution leads to defaults of other institutions. DebtRank denotes the risk of financial contagion from the interbank liability network. The default risk of a financial institution depends on its financial condition and on the economic situation in general. In principle, it can also depend on financial networks, for example, the network of overlapping portfolios or the network of firms and regions or industries. However, if network contributions to the probability of default are small (second order), it becomes possible to separate default risk from contagion risk, as given by DebtRank, in a meaningful way. Otherwise, it is necessary to replace or generalize DebtRank with a methodology that includes the network of overlapping portfolios and other relevant networks. In chapter 5 we show that DebtRank can be generalized for multi-layer networks to quantify SR originating from different financial markets, such as credit, derivatives, foreign exchange and securities. In future work we will conduct an empirical study on the network of overlapping portfolios and its implications for SR. Joint defaults can also be taken into account for example by copula methods. Once the default correlation has been estimated, it is possible to include the joint probability of default straightforwardly in the present framework. Joint defaults can be included by considering the joint probability of default of a group of financial institutions and by calculating the DebtRank for this group. Thus, additional terms containing the joint probability of default and the impact of a group can be added to eqs. (8.2) and (8.6).

We test the SRT within the framework of the CRISIS macro-financial model. The model produces SR profiles of banks that are practically identical with those of actual interbank liability data. Even on the level of individual transactions the model is fully compatible with empirical data. The SRT drastically reduces the probability for a financial collapse due to restructured liability networks that minimize the size of cascading failure. The tax is implemented in a simple way: an agent would like to make a transaction (with a given counterparty) and expresses this interest by announcing it (and the envisioned counterparty) to the Central Bank. The latter computes the SR increase associated with the transaction, based on the knowledge of the present state of the entire asset-liability network and the capitalization of its agents. The SR-increase is then presented to the agent as a tax (SRT) for that particular transaction. If the SR-increase is zero, there is no tax. The agent can now look for other counterparties to do exactly the same transaction. The agent will therefore typically screen several possible counterparties and then decide on the one with the lowest tax. Once the agent decides to carry out the transaction, it is executed and the tax is paid to the Central Bank or the government.

We show explicitly that SR is to a large extent a network property. We show that the SRT is able to restructure financial liability networks without loss of credit volume in the financial market. For the explicit comparison we implement and test a Tobin-like tax, which taxes all transactions regardless of their SR contributions. The Tobin-like tax does not restructure networks and only reduces SR because it also drastically reduces credit volume in the system. This is damaging as it makes the system less efficient; the loss of efficiency materializes as expensive credit for the real economy. We tested an alternative mode in which the SRT is set to the true increase in SR associated with the transaction, and not only a fraction ($\zeta = 1$). This alternative leads to much more homogeneous SR-spreading across all agents, and makes the system even safer, see fig. 8.2(b) and fig. 8.5(d), however, at the cost of much reduced transaction volume.

Since the SRT depends on both the interbank liability network and the equity capital, the SRT has both pro- and counter-cyclical effects. The pro-cyclical side arises through the fact that the SRT can bring systemically important banks under even more stress by reducing their scope for lending. However, the dependence of the SRT on the density of the liability network has a strong counter-cyclical effect. It is easy to see that the denser the interbank network, the higher the SRT rate becomes in general.

An obvious alternative to the SRT would be to identify SIFIs by a network metric, like the DebtRank, and directly tax them according to their systemic impact or increase the capital requirements similar to the briefly discussed

"SIFI surcharge". An immediate problem of a "bank tax" or a surcharge, compared to a transaction tax is that financial institutions sometimes have no control over their systemic impact. For instance, in case of publicly traded securities, such as bonds, financial institutions have no authority to decide who holds them and thus no influence on their systemic impact. Preliminary results in an ongoing simulation study indicate that a "SIFI surcharge" would reduce SR to a similar extent as in the FTT scenario.

We finally stress that the current market practice of not pricing SR into transaction costs effectively amounts to an implicit subsidy for those with the highest contribution to overall SR and an effective tax for those with the lowest.

Chapter 9

Summary

In this thesis we presented the results of four works already published [1, 2, 3] or in review at time of writing [4].

Chapter 5 is an empirical study of a financial multiplex network, which to our knowledge is based on the most detailed and comprehensive financial data currently available. In this chapter we quantify the daily contributions to SR from four layers of the Mexican banking system from 2007 to 2013. We show that focusing on a single layer underestimates the total SR by up to 90%. By assigning SR levels to individual banks we study the SR profile of the Mexican banking system on all market layers. This profile can be used to quantify SR on a national level in terms of nation-wide expected systemic losses. We show that market-based SR indicators systematically underestimate expected systemic losses. We find that expected systemic losses are up to a factor of four higher now than before the financial crisis of 2007-2008. We find that SR contributions of individual transactions can be up to a factor of one thousand higher than the corresponding credit risk, which creates huge risks for the public. We find an intriguing non-linear effect whereby the sum of SR of all layers underestimates the total risk. The method presented here is the first objective data-driven quantification of SR on national scales that reveal its true levels.

In chapter 6 we study propagation, diffusion, and synchronization mechanisms of SR under different regulation policies. We use a simple ABM of value investors in financial markets to test three credit regulation policies. The first is the unregulated case, which only imposes limits on maximum leverage. The second is Basle II and the third is a hypothetical alternative in which banks perfectly hedge all of their leverage-induced risk with options. When compared to the unregulated case both Basle II and the perfect hedge policy reduce the risk of default when leverage is low but increase it when leverage is high. This is because both regulation policies increase the amount of synchronized buying and selling needed to achieve deleveraging, which can destabilize the market. None of these policies are optimal for everyone: risk neutral investors prefer the unregulated case with low maximum leverage, banks prefer the perfect hedge policy, and fund managers prefer the unregulated case with high maximum leverage. No one prefers Basle II.

In chapters 7 and 8 we study the underlying dynamical mechanisms driving the link-formation process in complex financial networks. In these chapters we propose novel mechanisms that make a financial system safer in a self-organized critical manner. With a simple ABM we show in chapter 7 that SR in financial networks can be drastically reduced by increasing transparency, i.e. making the DebtRank of individual banks visible to others, and by imposing a rule, that reduces interbank borrowing from systemically risky nodes. This scheme does not reduce the efficiency of the financial network, but fosters a more homogeneous risk-distribution within the system in a self-organized critical way. The reduction of SR is due to a massive reduction of cascading failures in the transparent system.

In chapter 8 we further demonstrate that it is possible to quantify the share of SR that individual liabilities within a financial network contribute to the overall SR. We use empirical data of nationwide interbank liabilities to show that the marginal contribution to overall SR of liabilities for a given size is varying by a factor of a thousand. We propose a tax on individual transactions that is proportional to their marginal contribution to overall SR. If a transaction does not increase SR it is tax-free. With an ABM we demonstrate that the proposed SR Tax (SRT) leads to a self-organized re-structuring of financial networks that are practically free of SR. ABM predictions are in remarkable agreement with the empirical data and can be used to understand the relation of credit risk and SR. These chapters provide, to our knowledge, the first practical approaches for management of SR by re-shaping the topology of financial networks as outlined by Haldane and May [21].

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Zusammenfassung

Systemisches Risiko ist ein allgemeines Merkmal vieler komplexer Systeme. Die Wissenschaft Komplexer Systeme ist ein Forschungsgebiet, das generalisierten Wechselwirkungen zwischen Objekten, die von ihren Zuständen gekennzeichnet sind, untersucht. Typischerweise werden diese generalisierten Wechselwirkungen auf Netzwerkstrukturen vermittelt und führen zu einer extrem reichen Phasenstruktur, die oft komplizierter ist als die von physikalischen Systemen. Systemisches Risiko tritt in einer Vielzahl von natürlichen und vom Menschen geschaffenen komplexen Systemen als Konsequenz dieser Phasenstruktur auf. Es ist das Risiko, dass ein System global ausfällt, seine Funktion nicht mehr ausführen kann und mit möglicherweise dramatischen Folgen für das Gesamtsystem und seine Einzelteile kollabiert. Eines der wichtigsten Beispiele von systemischen Risiko ist heute das der Finanznetzwerke. Das Unvermögen systemisches Risiko zu quantifizieren birgt eine immense Gefahr für die Gesellschaft, und das Versäumnis systemische Risiken zu managen hat sich als äußerst kostspielig erwiesen. Systemisches Risiko hat sich zu einem Schwerpunkt der jüngsten wissenschaftlichen Forschung entwickelt, nicht nur wegen der gesellschaftlichen Bedeutung, sondern auch wegen der hochpräzisen Datenverfügbarkeit und der Tatsache, dass das Finanzsystem vom Menschen geschaffen wurde und im Prinzip verändert und verbessert werden kann. In dieser Arbeit entwickeln wir eine Reihe von praktischen neuen Methoden zur Quantifizierung und schließlich zum Management von systemischem Risiko. Um das Verständnis von systemischem Risiko voranzubringen, untersuchen wir Fortpflanzung, Diffusion und Synchronisationsmechanismen von systemischem Risiko nicht nur in einem einzelnen Finanznetzwerk, sondern auch in einer Überlagerung von Netzwerken, in so genannten Multiplex-Netzwerken. Wir präsentieren eine empirische Studie eines Finanz-Multiplex-Netzwerks, das nach unserer Kenntnis auf dem detailliertesten und umfassendsten Datensatz von einem Finanzmarkt basiert, der aktuell verfügbar ist. Die hier vorgestellten Verfahren sind die ersten objektiven datenbasierenden Quantifizierungsverfahren von systemischem Risiko auf nationaler Ebene. Durch die

Untersuchung der zugrunde liegenden Mechanismen der dynamischen Netzwerkbildung in komplexen Finanznetzwerken schlagen wir neue Methoden vor, die Finanzsysteme auf eine selbstorganisierte kritische Weise sicherer machen. Diese Arbeit liefert den ersten praktischen Ansatz für das Management von systemischen Risiken durch Umstrukturierung der Topologie eines Finanznetzwerkes. Wir stützen unsere Untersuchungen sowohl auf hochwertige Daten von Zentralbanken, als auch auf agentenbasierte Modelle, die im Rahmen dieser Arbeit entwickelt wurden.

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Publications

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1. S. Poledna, Agent-based models in econophysics: applications to financial regulation, Diploma thesis, 2011

Talks

2015 OECD Workshop on Complexity of the Economy: Research and Policy Implications, OECD Headquarters, Paris, France, Elimination of systemic risk in financial networks by means of a systemic risk transaction tax

2015 1st Vienna Conference on Pluralism in Economics, Vienna University of Economics and Business, Austria, Elimination of systemic risk in financial networks by means of a systemic risk transaction tax

2014 CRISIS Final Workshop: A Complexity view of Crisis, Milan, Italy, Central banking and regulation of systemic risk

2014 European Conference on Complex Systems (ECCS) 2014, Satellite: Multiplex Networks 2014, Lucca, Italy, Multiplex structure of systemic risk in financial networks

2014 NetSci 2014, Berkeley, USA, Elimination of systemic risk in financial networks by means of a systemic risk transaction tax

2014 Computing in Economics and Finance (CEF) 2014, Oslo, Norway, Elimination of systemic risk in financial networks by means of a systemic risk transaction tax

2014 Deutsche Physikalische Gesellschaft (DPG), Frühjahrstagung: Sektion Kondensierte Materie 2014, Dresden, Germany, DebtRank-transparency: controlling systemic risk in financial networks

2013 European Conference on Complex Systems (ECCS) 2013, Barcelona, Spain, DebtRank-transparency: controlling systemic risk in financial networks

2013 International conference on statistical physics of the International Union of Pure and Applied Physics 2013 (STATPHYS 25), Satellite: Financial Networks and Systemic Risk, Kyoto, Japan, DebtRank-transparency: controlling systemic risk in financial networks

2013 Econophysics Colloquium 2013, Pohang, Korea, Leverage-induced systemic risk under Basle II and other credit risk policies

2013 NetSci 2013, Copenhagen, Denmark, Systemic risk in financial networks: DebtRank transparency

2011 European Conference on Complex Systems (ECCS) 2011, Econophysics Colloquium 2011, Vienna, Austria, The role of leverage in a world of perfect hedging

Media coverage (selection)

2015 May	Wiener Zeitung: future, Risikosteuer für Spekulanten
2014 November	Süddeutsche Zeitung, Mehr Stabilität für Finanzmärkte - Die bessere Steuer
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