Banking regulation and network-topology dependence of iterative risk-trading games

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Abstract

In the context of understanding risk-regulatory behavior of financial institutions we propose a general dynamical game between several agents who pick their trading strategies depending on their individual risk-to-wealth ratio. The game is studied numerically for different network topologies. Consequences of topology are shown for the wealth time-series of agents, for the safety and efficiency of various types of networks. The model yields realistic-looking time-series of wealth and the cost of safety increases as a power-like function. The relevant model parameters should be controllable in reality. This setup allows a stringent analysis of the effects of different approaches of banking regulation as currently suggested by the Basle Committee of Banking Supervision. We find evidence that a tightening of the current regulatory framework does not necessarily lead to an improvement of the safety of the banking system. Moreover, the potential impact of catastrophic events like September 11, 2001, on the financial system can be measured within this framework.

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INTRODUCTION

The efficiency and stability of the financial system and its institutions is seen as one of the core elements of a modern economy. The regulation of financial intermediaries is thus a central issue which raises a number of open questions both for practical implementations and for academic research. During the past two decades an intensive discussion about the regulation of financial markets evolved mostly driven by media attended events like the 'Russian crisis' in 1998 and defaults of big financial institutions like the failure of Barings Bank or, more recently, Long Term Capital Management. This discussion formed the basis for a regulatory innovation process under the lead of the Basle Committee of Banking Supervision which sets the relevant legal regulatory framework for the G-10 economies as well as for the EU. As a consequence of the US Savings & Loans disaster in the mid-eighties the first milestone of this process was the first Capital Accord in 1988 (Basle I) which forced banks to hold a 8% of total assets capital cushion to prevent default due to extreme unexpected losses. This was the first step where the activities of financial intermediaries were limited by the risk (measured by total assets) of their positions. Since total assets is an insufficient measure of risk at least for trading positions in securities and derivatives, the 1995 Amendment to the Capital Accord introduced a more risk-sensitive framework for market risk activities. Finally, the second Capital Accord (Basle II) which currently is under consultation is aimed to introduce a risk-sensitive framework for credit risk as well.

Although the discussion about the cornerstones of the new regulatory framework is in its final phase, there are a number of open questions remaining for the future. Firstly, if the activities of financial intermediaries are limited by the risk of their current positions, how should risk be measured? Secondly, if a capital cushion relative to the risk run by a bank is needed, what is its optimal size? Further, does a specific risk-sensitive framework lead to undesirable pro-cyclical effects in the economy? Finally, is this risk-regulatory framework sufficient to prevent the financial system from a total collapse when catastrophic events like September 11, 2001, occur?

It is the main purpose of this paper to address these questions and to develop a formal framework which allows a stringent analysis of the effects of different approaches of banking regulation. Moreover, the potential impact of catastrophic events like September 11 on the financial system can be measured within this framework. To achieve this goal we propose a general dynamical game between several agents (banks or financial intermediaries) who build their trading strategies depending on their individual risk-to-wealth ratio. The general structure of the suggested framework allows to model the decisions of the agents without resorting to a specific utility-model. Therefore, our results do not depend on the choice of a specific utility-based framework. The financial system is modeled using different network topologies which enables us to explicitly measure the network-topology dependence of different regulatory actions and various other important factors. This is a major contribution to the existing research because to our knowledge this is the first attempt of an analysis of financial markets where dynamic game models and network-topology are combined. Differing effects of single bank defaults and regional banking crises can easily be captured by our model. Additionally, the chosen network topology can be used to mimic specific structures of several national banking systems like "sectors" or risk-sharing cooperations (e.g., "Genossenschaftsbanken").

This research is related to the discussion about systemic risk in the banking sector, see [1, 7, 15]. The authors of [1] empirically examine systemic risk in the Italian interbank clearing network where they explicitly address the potential size of a "domino effect" where the default of a single bank may jeopardize the ability of "neighbor" banks to meet their obligations. A first attempt to model systemic risk in financial networks was undertaken in [7] where the authors show comparative statics describing the relationship between the clearing vector and the underlying parameters of the financial system which is exposed to external stochastic shocks. However, they model the behavior of financial institutions purely deterministically and they do not examine potential effects of network topology. A third stream of research, e.g. [15], focuses on the default correlation of banks as the central parameter of measuring systemic risk or contagion in the banking sector. The framework suggested in this paper enables us to analyze contagion as well as "domino effects" and provides a profound basis for comparative statics with respect to the architecture of the financial market combined with the regulatory framework.

THE MODEL

The aim of this work is to develop a simple model of a network of banks or financial institutions who can trade risk amongst each other in a game-theoretical setting. Banks are forced to enter risk through demands of their clients, but try to compensate it amongst each other. We introduce an iterative dynamical game where players (banks) can choose between different strategies, depending on their need to reduce individual risk. The need to reduce risk depends on the wealth of a bank and regulatory parameters. The game takes place between players whose connections are characterized by a certain graph topology. We introduce measures which characterize the performance of different network topologies with respect to overall fairness and stability of the network, individual safety, i.e. survival probability, and the efficiency of reducing exogenous, i.e. externally enforced, risk. By studying the time evolution of the wealth of interacting players we find remarkable coincidence with realistic financial time-series. Characteristics of those time-series differ drastically depending on topology. It is important to mention here that in contrast to some recent approaches in cooperative network- and game theory, see e.g. [4, 5, 20, 23], our agents do not learn but are purely selfish. In our setting they do not have any incentive to adapt for cooperation.

In the following we deal with a set of N sites (representing banks) labeled by $i = 1, \cdots, N$ who receive requests from their N exterior clients (for simplicity each bank has only one client). These requests (forwards, swaps, weather derivatives, etc.) are modeled by bets which depend on an external random process $X(t)$, say the weather, and a time of maturity t_m. For the rest of this paper we consider a simple binary random process $X(t) \in \{-1, 1\}$ with equal probabilities $p(-1) = p(1) = \frac{1}{2}$. For example, a client today bets 20 m USD that on $t_m =$ Dec. 15^{th} 2004 there will be rain. The bank has to accept these external bets and receives an incentive, inc^{exo}, for it (transaction costs). At each timestep in the game, exterior clients confront their banks with external bets with uniformly distributed times of maturity, $t_m = t + \tau$, $\tau \in \{0, 1 \cdots, \tau^{\max}\}$, where t denotes present time. For two players only, compare e.g. with [11, 21]. The associated betting volume offered to bank i is a random number also drawn from a uniform distribution $B_i^{exo}(t+\tau) \in [0, D(t) \cdot W_i(t)]$, where $W_i(t)$ is the present wealth of bank i. This means that the maximum betting volume asked from a bank is proportional to its present wealth (the smaller the banks the smaller their transactions). D is the percentage of external risk a bank is allowed to take within a given time step, with respect to its own wealth. D could be seen as a regulatory parameter since it imposes an upper limit for a bank's risk dependent on its wealth (or equity in a wider sense). This parameter does not yet resemble the 8%-rule currently set by regulators, where some risk measure (e.g., risk-weighted nominal value of positions) must not exceed the 12.5

multiple of a bank's equity. Rather, D can be understood as a measure that prevents banks to accept large risks within short time. The 8%-rule will be incorporated in the model later (see below). Since in case of no interactions, D would simply be the diffusion constant of a Brownian motion, we will call D a diffusion constant.

By accepting a bet, bank i enters risk $R_i(t+\tau)$, which is defined as the maximum amount the bank can loose at time $t+\tau$, i.e. $R_i(t+\tau) = |B_i^{exo}(t+\tau)|$. This risk measure is related to a great variety of risk measures used by regulators, e.g., the standard deviation of profit and losses (volatility), and the 1%-quantile of the profit and loss distribution (value-at-risk). Now, the essence of the game is that this risk can be traded away, if the bank is able to find a neighbor bank, which is willing to enter a betting contract which serves to reduce this risk. In the above example, the bank will either look if an appropriate bet is already offered on the "market" (issued by a neighbor bank), or it will issue one itself to its neighbor sites, which would read: 20 m USD that on t_m = Dec. 15$^{\text{th}}$ 2004 there will be sunshine. All the contracts are kept in the "betting book" $B_{ij}(t+\tau)$, which contains the betting volume bank i is betting against bank j at time $t+\tau$. If bank i offers a bet at $t+\tau$ it does so through an entry in the "market" book $M_i(t+\tau)$. The numerical value of M_i is the volume. The market book is "visible" to all neighbor banks of i only. Whenever a bank agrees to a bet, the offering party is obliged to pay an incentive (*inc*) to the accepting bank. We choose *inc* to be 10 % of the bet volume $B_{ij}(t+\tau)$.

If a bank finds a bet on the market (offered by a neighbor site) which serves to reduce its risk it will accept it and receive the incentive for the deal. This we call the *passive strategy*. On average, the bank will gain the incentive for sure and then await the outcome of the bet, where there is a fair 1:1 chance to win. In case there is no offer in the market book, and the risk of bank i is high with respect to its present wealth $W_i(t)$, it will offer a bet itself to its neighbor banks, which we call the *active strategy* (insurance is only bought if really needed, i.e. if risk-taking can not be afforded). After entering a contract, risk is still defined as the maximum amount the bank can loose at a given time $t+\tau$, but now consists of the external bets and all the bets entered with neighbor sites, i.e., $R_i(t+\tau) = \left|B_i^{exo}(t+\tau) + \sum_j B_{ij}(t+\tau)\right|$, where j indexes the neighboring banks. The strategy of all banks is always passive, if possible, and only becomes active if the risk/wealth ratio is high. To model this we define the probability density for bank i of current wealth $W_i(t)$ to adopt an active strategy to reduce risk at time $t+\tau$ by

$$p_i^{\mathrm{active}}(t,\tau) = \exp\left[-\alpha \frac{R_i(t+\tau)}{W_i(t) - inc}\right] \quad . \tag{1}$$

The interaction between banks is thus not fully deterministic. Here α is a constant which controls the "riskiness" of players. It was kept constant $\alpha = 5$, for all following computations. In contrast to previous work, e.g., [7], we introduce a noise component into the behavior of agents which replaces the role of the utility function in the decision making process. Whereas from a single-agent perspective this might be regarded as an arbitrary approximation, from a regulator's perspective, however, this model seems realistic, because the regulator faces a large number of agents with different utility functions which are not known by the regulator. Thus, our decision making rule (1) explicitly models the uncertainty about the single-agent utility functions, or put equivalently, models the stochastic deviations of the decisions of single agents from the representative agent.

To explicitely model the Basle regulatory framework, the probability for adopting an active strategy is always equal to one, whenever the total risk exceeds a certain percentage of wealth, i.e. $\sum_\tau |R_i(t+\tau)| \geq L_{\mathrm{Basle}} \cdot W_i(t)$. Presently, the actual Basle parameter L_{Basle} is 12.5, but is an open parameter in the model. Note, that the restriction to act it $\sum_\tau |R_i(t+\tau)| \geq L_{\mathrm{Basle}} \cdot W_i(t)$ only enforces the agent to adopt the active strategy, i.e. to place an order to the market. It is possible, however, that the order is not fulfilled because there is no counterparty willing or able to accept the bet. Under this scenario the actual risk of the bank will exceed its regulatory boundary. This scenario is thus related to a (at least local) banking crisis where due to a lack of liquidity in the market banks are not able to reduce the risk of their positions even when they are forced to by regulators. This feature of our model allows to capture propagation of illiquidity effects comparable to what happened during the Russian crisis in 1998.

Each of the N players who participate in the game is represented by a node or site. Sites are connected by links, which are non-zero entries of the interaction-graph matrix, G_{ij}. A value of $G_{ij} = 1$ means site i has a connection to site j, $G_{ij} = 0$ means no connection. Players which are connected by links are called neighbors and can interact with each other. In the following we shall study the particular classes of six different network topologies which are shown in Fig. 1. The connectivity of these graphs, defined as the average number of links per site $C = \langle \frac{\#\mathrm{links}}{\mathrm{site}} \rangle$, model the efficiency of "information flow" in the network, a low connectivity C means high "market friction".

At the beginning of each timestep, the external bets are offered to the banks. Each bet carries a time of maturity from now (t) till τ timesteps in the future. As a maximum future date for bets we chose $\tau^{\max} = 10$ timesteps. The total exogenous risk entering at this stage at time t is $R^{\mathrm{exo}}_{\mathrm{total}}(t) = \sum_{i,\tau} B_i^{exo}(t+\tau)$. After this exogenous update the sites are run through in a random asynchronous update. Once a site i is chosen, the routine goes through all of its neighbor sites j (determined by G_{ij}), again in randomized order. The actual game between the pair (i, j) now takes place:

Bank i checks in the market book if any bets are available from bank j for all times τ which can reduce i's risk, i.e., $|R_i(t+\tau) - M_j(t+\tau)| < |R_i(t+\tau)|$. If that is possible the deal will be accepted and i will receive the incentive from j. The betting book is now adjusted according to the terms of the deal, i.e., $B_{ij}(t+\tau)$ now becomes $B_{ij}(t+\tau)+M_j(t+\tau)$. If no more passive strategies are possible i decides – according to Eq. 1 – if it will issue an offer itself by placing an entry in the market book of size $M_i(t+\tau) = R_i(t+\tau)$. If an other bank will (later) accept this bet, i will then pay the corresponding incentive and be then free of risk. After all sites have been run through, all the bets of today (t) will be settled according to the random outcome of $X(t)$. The wealth update now is nothing but,

$$W_i(t+1) = W_i(t) + X_i(t) \cdot \left(B^{\mathrm{exo}}(t) + \sum_j B_{ij}(t) \right) \quad , \tag{2}$$

since all incentives have been taken care of along the way.

A bank is said to be defaulted if its wealth falls below zero. It will then be eliminated from the network, together with all the links tying it to its neighbor sites. Also all future entries in the betting book will be eliminated as well, the partner sites will neither pay lost bets to the defaulted site nor will they receive what they would have won. So default of a site can be good or bad for partner sites, depending on the the exterior process $X(t)$. Any open payments of the defaulted bank to external customers will be shared by all the remaining banks. This resembles the function of a deposit insurance system to some extent. A default of a neighbor site can be disastrous for a bank however, since it becomes rapidly exposed to external risk again, which can be high, and in case of a bad outcome of $X(t)$ can cause its own default as well. In this context spatial catastrophe-spreading can be studied dynamically.

RESULTS

We implemented the above model for $N = 36$ sites to stay within reasonable computing times. For simulations of the regulation effects we used $N = 100$ banks for networks with low connectivity C. The external incentive was set $inc^{\text{exo}} = 0$, in order to keep things as transparent as possible and not be disturbed by externally enforced drifts. As the initial condition we set $W_i(0) = 1$, for all i.

Network Effects

In order to estimate the effects of different network topologies on the game, in a first set of simulations we set the Basle parameter L_{Basle} to infinity, i.e. it will not play any role. We first analyze the time-series of the wealth processes. In Fig. 2 (a) and (b) we show the wealth trajectories of the 36 sites over 200 timesteps for a diffusion constant $D = 7$. The latter was chosen to avoid defaults during this run. The 1D lattice (left row) is compared to the fully connected graph (right). The difference due to network topology is visible by plain eye. The fully connected graph appears to keep the sites at more or less the same level of wealth, while for the badly connected topology some sites become "rich" and some are at the edge of disappearing. The fully connected graph provides a "fair" basis for all sites. In Fig. 2 (c) and (d) the log-return of the wealth process, $r_i(t) = \log(W_i(t)) - \log(W_i(t-1))$, is shown, again for all sites. It can be seen that for the fully connected net the average spread in returns is significantly smaller, the market is less volatile. The log-return is frequently used in financial time-series, and – for efficient and complete markets (which is unrealistic) – is often assumed to be Gaussian [9]. The corresponding distributions for the two runs are shown in 2 (e) and (f). The log-return distribution of the fully connected network is clearly "more" Gaussian for small r_i, but still has large outliers (fat tails). Fat tails are a well known phenomenon in financial time-series [3, 6, 17, 19], which has been addressed in a number of physical models recently, see e.g. [8, 10, 13, 14, 18].

In Fig. 3 we present the number of defaults as a function of connectivity, occurred during a simulation with a diffusion constant $D = 10$ (a). All the data and errors shown in the figure are mean values and standard deviations from 50 independent simulation runs, each a 100 timesteps long. The spread is defined as the variance of wealth of the N sites at the latest time in the simulation (100 timesteps) and is shown in (b). Volatility is defined as

$$V = \sum_{i,t} |r_i(t)| \quad , \tag{3}$$

and is a measure of trading activity in a market (c). All of these above measures show a clear drop as the number of links per site rises, i.e. as the connectivity of the network, or the risk flow or "permeability" increases. It seems reasonable to define an index of efficiency of the network, which relates the risk imposed by the exterior clients to the risk the banks are left with after risk-trading (at the end of the trading day):

$$E(t) = \frac{R^{\rm exo}_{\rm total}(t) - \sum_i R_i(t, \text{ after trades})}{R^{\rm exo}_{\rm total}(t)} \quad . \tag{4}$$

If all the risk is compensated $E = 1$, if trading did not have any risk-reducing effect, it should equal zero. The corresponding curve is given in Fig. 3 (d), and shows that the efficiency of the network increases from about $E = 0.74$ to $E = 0.92$. In (e) we show the ratio of active to passive strategies as adopted by the players during the run. It is seen that for the poorly connected topologies sites are forced to be more active since they face high risk/wealth ratios. As a measure for overall safety in the various networks we looked at the mean first-default-times in separate runs for various values of the diffusion constant D. The mean first-default-times are averages over the timesteps in the simulation until the fist default occurs. 1000 independent runs have been performed; random graphs have been additionally averaged over 10 different random topologies. A clear power law is seen when plotted in a log-log fashion, as in Fig. 4. The corresponding power exponents for $D = 0.20$, 0.15, and 0.13 are 0.21, 0.42, and 0.56, respectively.

In a set of simulations we observed contagion effects. Contagion means that the default of a given bank significantly increases the default probability of its neighbors. In many scenarios the default of neighbors is realized and local "banking crises" can be observed. To model effects like September 11 we artificially removed a single large bank from the network. The spread of the crisis depends heavily on the network topology, and ranges from small, locally bounded events to the total collapse of the network. Since these results are hard to visualize over the time course we do not present them in this version of the paper.

Basle Parameter Effects

Now we bring the Basle parameter L_{Basle} down to finite values and study its effects on network safety. As a measure of safety we again take the mean first default time as defined above. For a fixed value of D we run simulations for different values of L_{Basle}. To study the effects of network type we perform the runs for the 1D and 2D regular lattices with a connectivity of 2 and 4 respectively. These runs contained 100 banks, so that higher connectivity was beyond reasonable computation time. Results are given in Fig. 5. First default time, which is an inverse measure of network risk, generally decreases with increasing Basle multiplier L_{Basle}. As one would expect, a lower value of L_{Basle} – which is equivalent to a higher capital cushion – reduces the risk of the system.

One of the most interesting findings of this paper is the existence of two plateaus, one for low and one for high values of L_{Basle}. This seems to be independent of network structure. From a regulator's point of view, this means that there are regions of the multiplier L_{Basle}, where a seemingly strong reduction of the regulatory parameter has vanishing or even zero effect on the safety of the system. It could be interesting for regulators to know in which region the current regulatory framework is located.

The strong (power like) decay from one plateau to the other is often related to a phase transition in physics. This means the existence of two stable regimes (where regulatory activity has no effect) which can change from one state to the other within a relatively small critical region. Whenever a phase transition is present powerful mathematical tools from statistical physics can be applied and used to describe such systems.

We found that a change in parameter D results in a parallel shift of the curves and does not alter the basic characteristics of the findings.

DISCUSSION

To summarize, we have introduced a relatively simple model of interacting agents who change their modes of interaction (strategy) according to their state of being, i.e. their need to reduce risk. The basic model is inspired from the structure of the well-known iterated prisoner's dilemma [2, 12], where two players are equipped with two possible actions, see also [24]. In our case the pay-off matrix additionally depends on an external process, and the size of bets, which in our model is a dynamical variable. Our model contains very few parameters, three of which, the connectivity C, the diffusion parameter D, and the regulatory (Basle) parameter L_{Basle} are the relevant ones. We have checked that the remaining parameters α and $\tau_{\max}$ play a comparably irrelevant role which we do not discuss here. We have performed several runs with various sizes of N to check for finite size effects. We found that for N smaller than about 20, scaling starts to vanish. Our main results are that in a number of crucial measures there exists a very sensitive dependence on the connectivity (which models the market structure in the real world). We find that in well connected networks almost no spread of wealth is able to develop and that topology alone can lead to "fair" networks. Highly connected networks show significantly less large moves in wealth changes (less volatility), the market becomes less hectic. Distributions of the log-returns are "more" Gaussian, but still show realistic fat tails. Well connected networks are more efficient in reducing global risk, and show significantly fewer defaults. The average first default time (inverse safety) increases with connectivity as a power with exponents smaller than 1. If connectivity is associated with costs for the agents, this demonstrates that safety becomes extremely costly (power-like) as higher levels of safety are required. We are currently investigating the same model in a small-world network setting [22].

We finally remark that the parameters C, D, and particularly L_{Basle} can be controlled by central banks and governments in reality to regulate risk [16]. It is a major finding of this paper that the requirement of a capital cushion in the form of the Basle multiplier L_{Basle} as currently used by regulators may have unexpected adverse effects. We found that for some L_{Basle} a seemingly strong reduction of the regulatory parameter has vanishing or even zero effect on the safety of the system. This may lead to unjustified overconfidence in the regulatory action. It may also lead to unnecessary restrictions to economic activity, because a relaxation of the Basle multiplier would not lower the safety of the system. The next stage of the analysis should focus on a more detailed inspection of the interrelation of the model parameters and on the calibration of the model to real world data.

Even though our model is phrased in terms of a game between banks who insure themselves by trading financial assets the model should be very general and be applicable not only to the theory of financial markets, but also to a wide variety of interacting complex systems.

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FIG. 1: Schematic plot of different graph topologies. (a) One site is connected to all the other $N-1$ sites (monopoly). (b) Each site is connected to two neighboring sites (1-D circle, with periodic boundary) (c) Each site is connected to four neighboring sites (regular 2-D lattice, with p.b.) (d) Random lattice: Each site is connected to a random other sites, the average number of links per site is fixed. "Random 0.222" means that on average 22.2% of all possible ($N \times N$) links are present. (e) Same as before with "Random 0.444", i.e. 44.4% of $N \times N$ possible links are realized on average. These numbers are chosen to to provide a connectivity of $C = 8$ and 16 links/site on graphs with $N = 36$ sites. For the random graphs we checked that they were complete, i.e. every site could be reached from every other site. (f) Each site is connected to all the other sites (fully connected).

FIG. 2: Comparison between the 2D (left) and the fully connected (right) topologies. Top: Wealth trajectories for the 36 sites. Middle: Log-returns $r_i(t)$ of the sites plotted on top of each other. The volatility for the fully connected graph is much less. Bottom: Distribution functions derived from histograms of $r_i(t)$ (points). The line is a Gaussian function with the same mean and standard deviation as the sample of r_i. Clearly the fully connected graph is "more" Gaussian, though it still has fat tails.

FIG. 3: Performance measures as a function of the different topologies. From top to bottom: number of defaults occurred within the first 100 timesteps; spread (standard deviation) of the wealth distribution at timestep 100; volatility estimate; efficiency parameter; ratio of active strategies over passive ones within 100 timesteps.

FIG. 4: Mean time till the first default occurs, as a function of graph topology. We show the situation in a for several values of the "diffusion constant" D and find clear power law behavior. Errors are less than symbolsize.

FIG. 5: Mean of the first default times as a function of the regulatory Basle multiplier. Symbols represent mean values from 100 independent simulation runs with 100 banks for two different types of networks. Mean errors are less than twice the symbolsize, and are not shown for clarity of the plot.

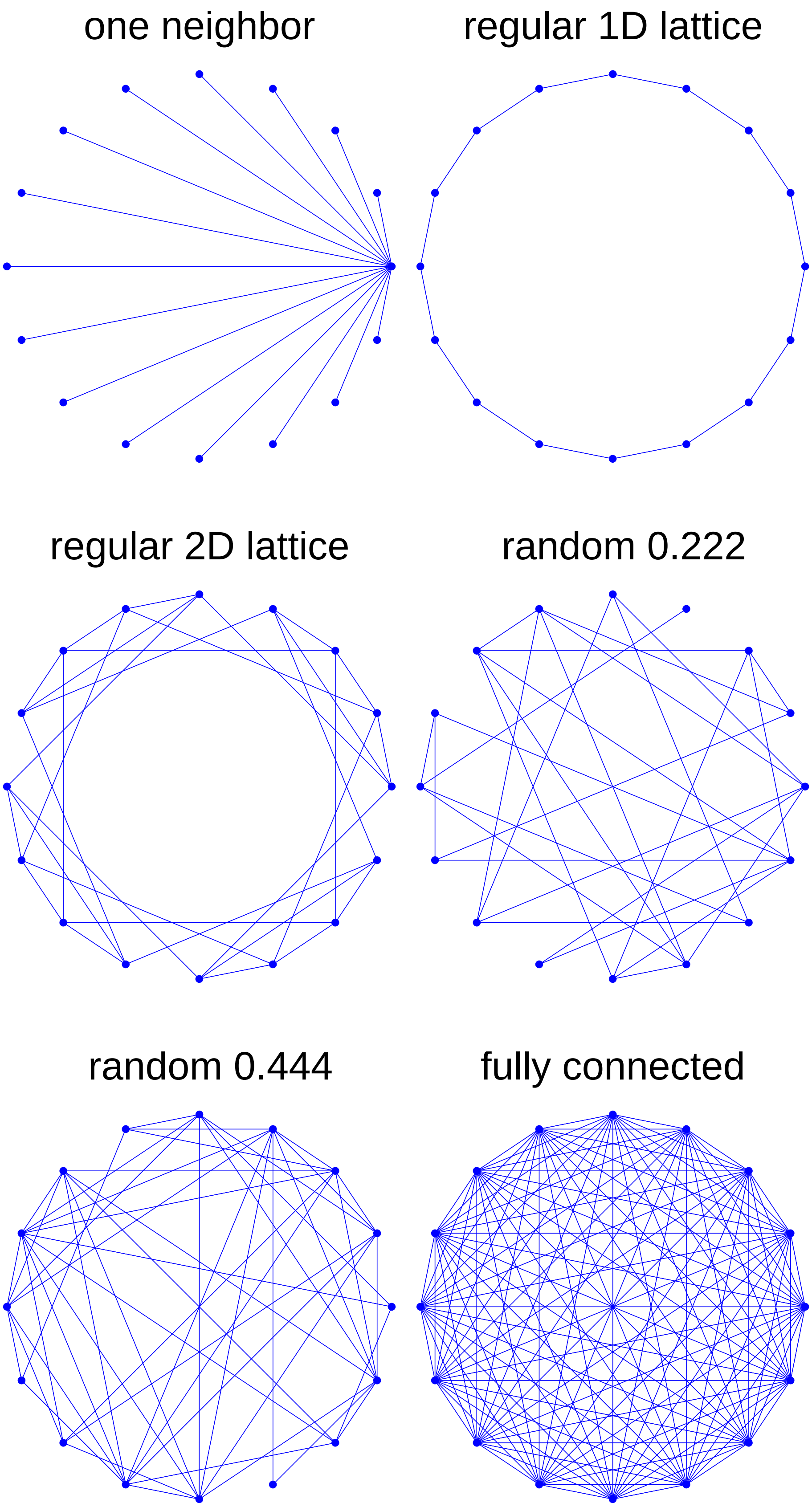
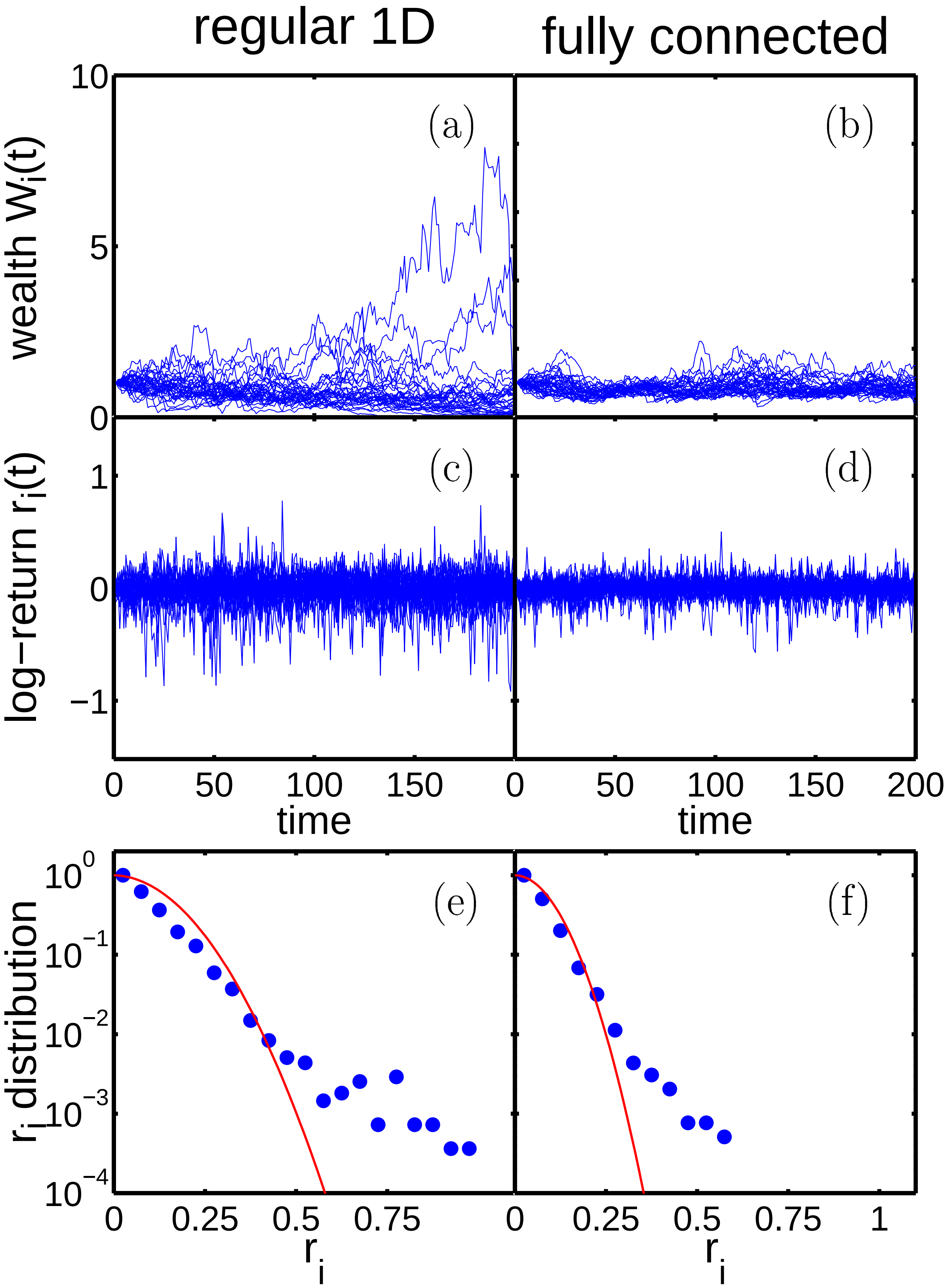
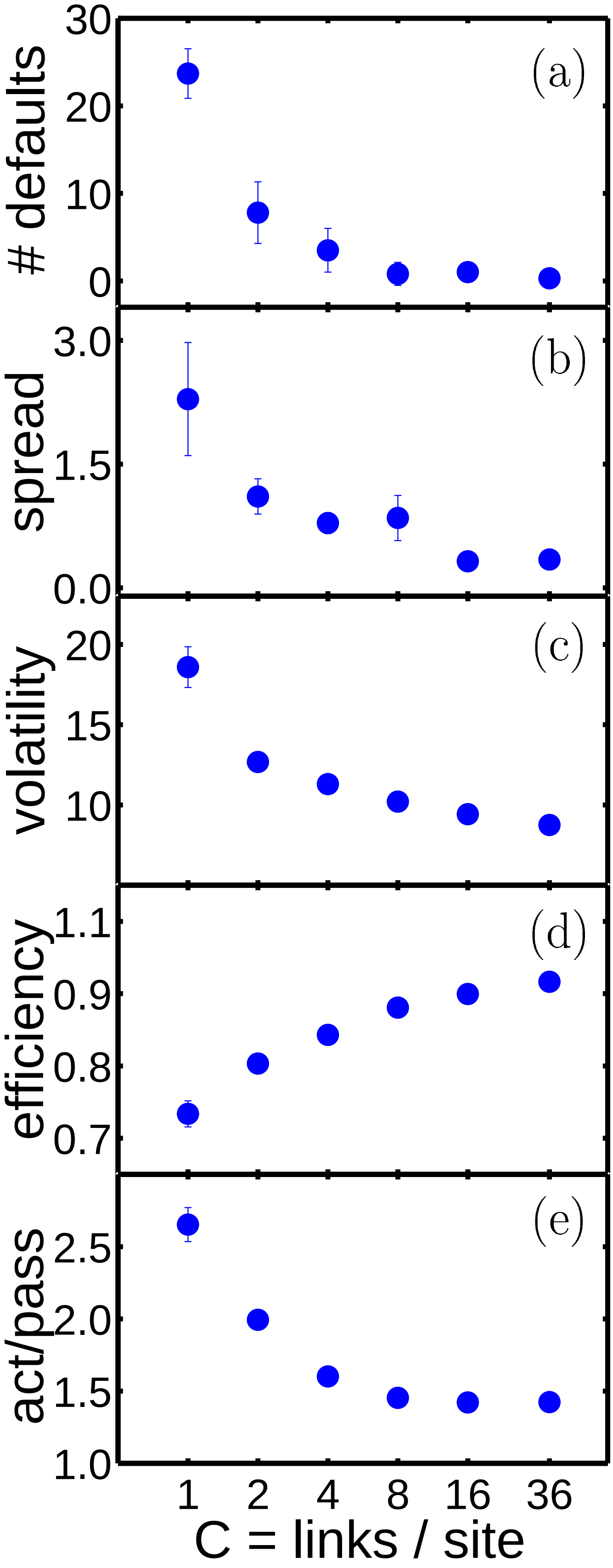

one neighbor
regular 1D lattice
regular 2D lattice
random 0.222
random 0.444
fully connected

FIG. 1



regular 1D
fully connected
(a)
(b)
(c)
(d)
(e)
(f)
wealth $W_i(t)$
log−return $r_i(t)$
r_i distribution
time
time
r_i
r_i

FIG. 2



defaults
(a)
30
20
10
0
spread
(b)
3.0
1.5
0.0
volatility
(c)
20
15
10
efficiency
(d)
1.1
0.9
0.8
0.7
act/pass
(e)
2.5
2.0
1.5
1.0
1
2
4
8
16
36
C = links / site

FIG. 3

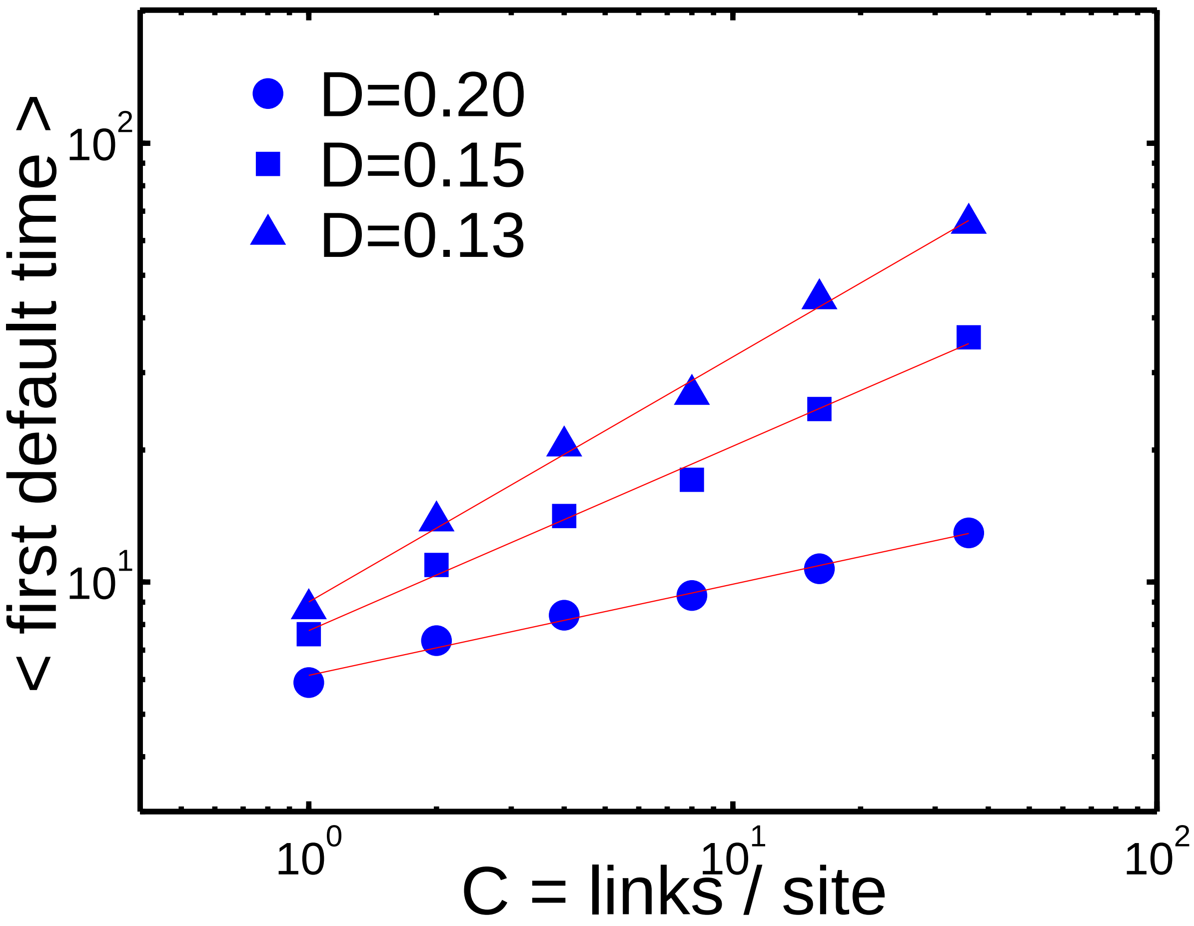
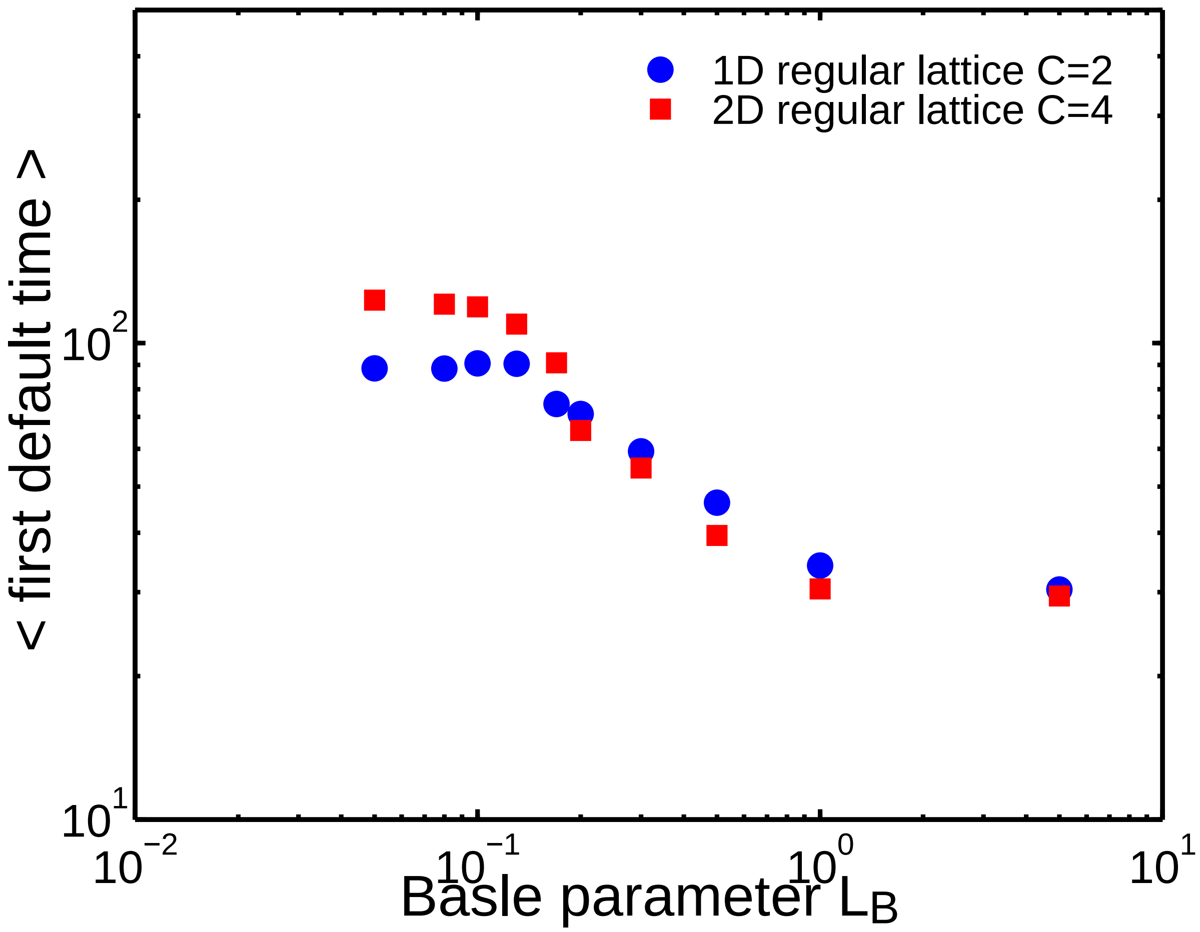

D=0.20
D=0.15
D=0.13
< first default time >
10^2
10^1
10^0
10^1
10^2
C = links / site

FIG. 4



1D regular lattice C=2
2D regular lattice C=4
< first default time >
Basle parameter L_B
10^1
10^2
10^{-2}
10^{-1}
10^0
10^1

FIG. 5