Early Warning Signals in Banking Networks

And their relations to Ecology

Introduction

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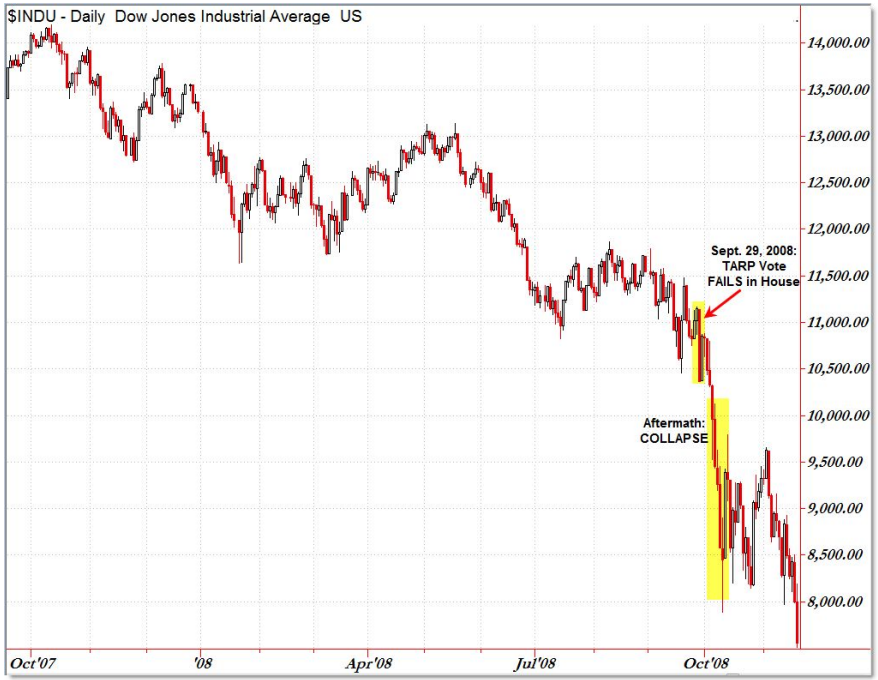
According to Richard Lambert, the removal of the ceiling on loans and reduction of bank’s liquidity requirements triggered the secondary banking crisis of 1973-74[2]



2008 Subprime Crisis

1929 Great Depression

Critical Transitions

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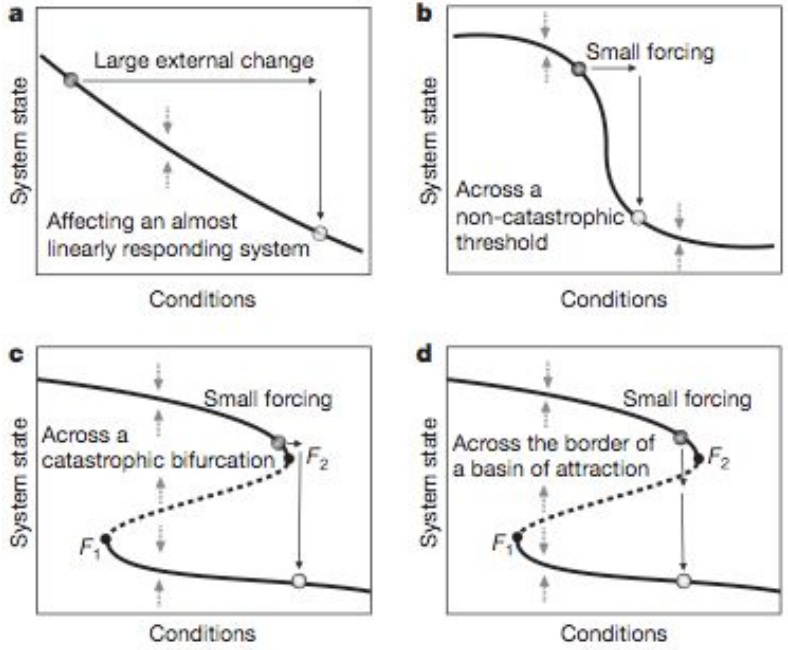

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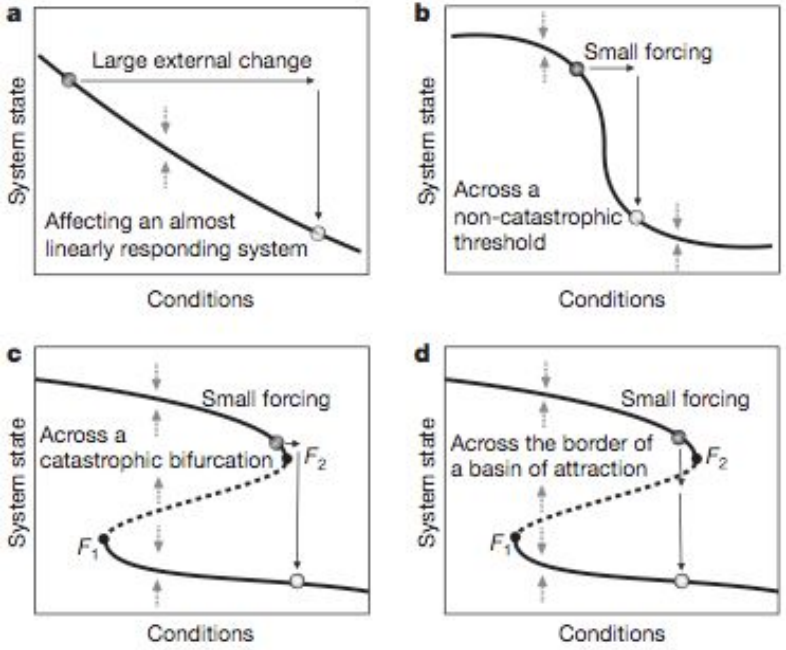
- These transitions are observed in many natural systems such as climatic and ecological systems.
- Early warning signals and mitigation strategies are highly sought.



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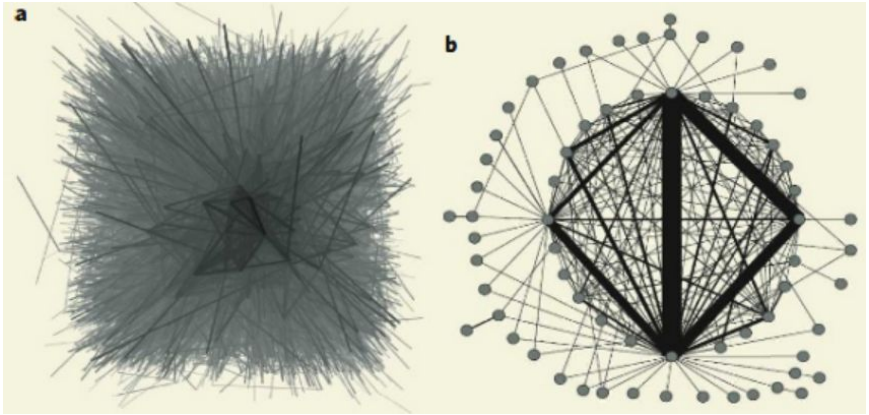

A network comprising thousands of banks

Core of the Network

Image sourced from Ecology for Bankers, May et al, Nature

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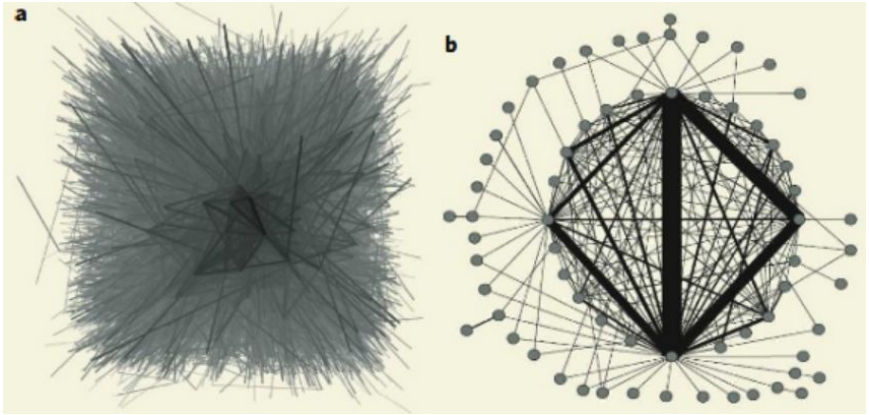

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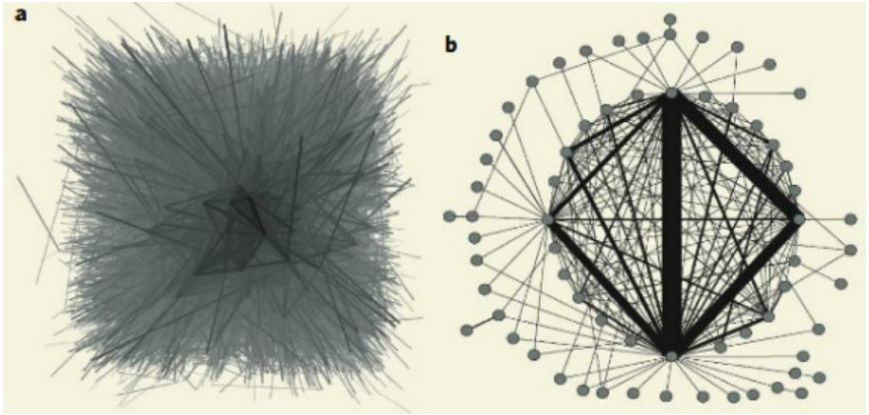
- Despite its simplicity, it shows a variety of interesting features.



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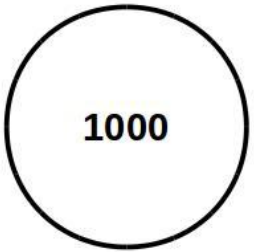
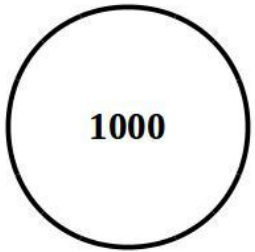
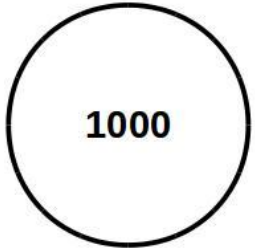
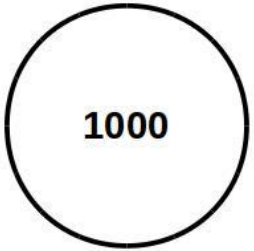
- After the links are made, each bank distributes $\boldsymbol{l}$ equally among all its neighbours.

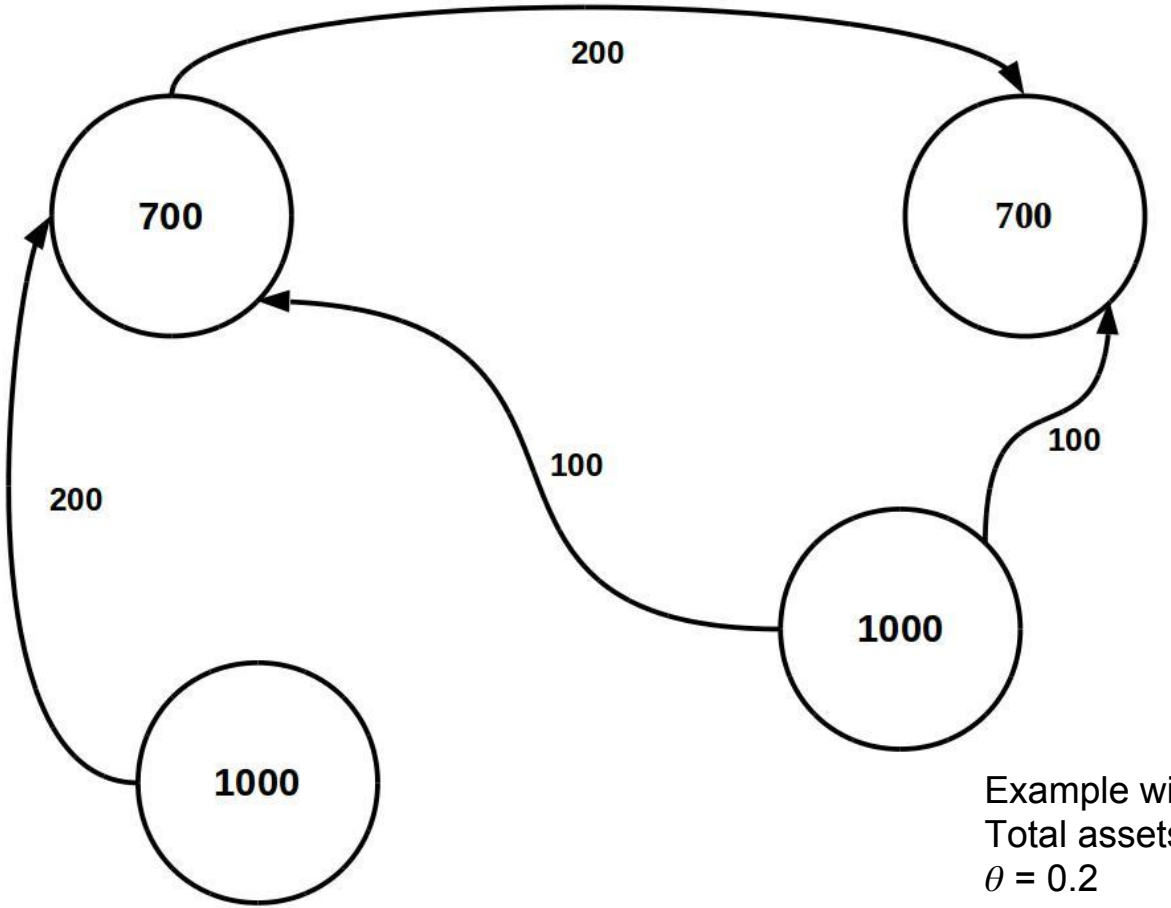








Example with four banks:
Total assets = 1000 units.
θ = 0.2



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- In this manner, a shock propagates throughout the system until it becomes small enough to do no harm.

Parameters to vary

- The model starts out with four parameters which we can possibly set:
  a. The starting assets: $\boldsymbol{a}$
  b. The lending ratio: $\boldsymbol{\theta}$
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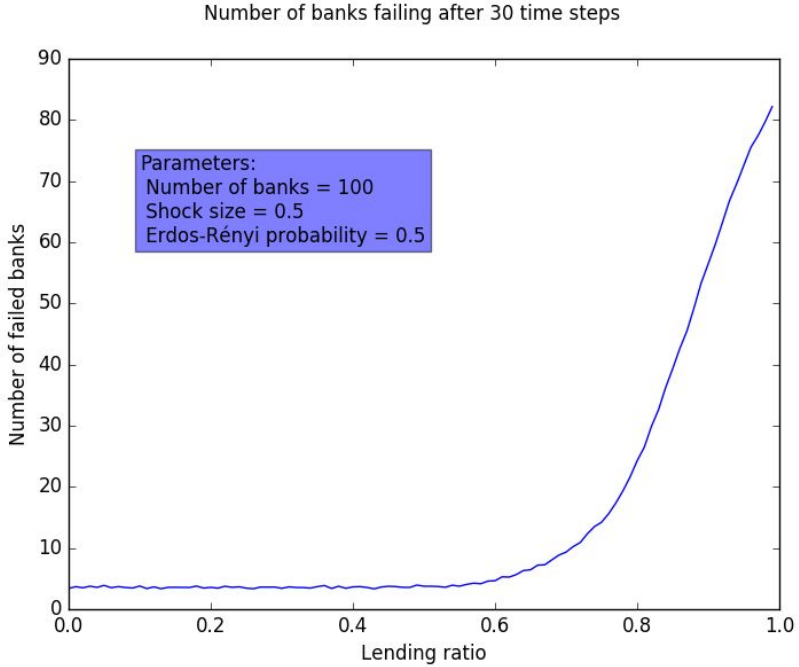
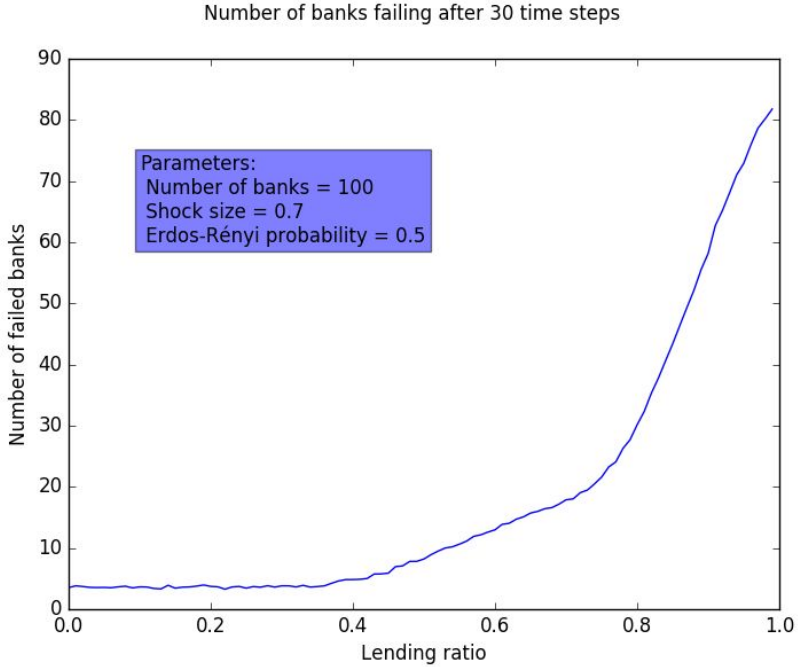
- That leaves us with just three parameters to vary: $\boldsymbol{\theta}$, $\boldsymbol{p}$, and $\boldsymbol{f}$.

Varying the lending ratio





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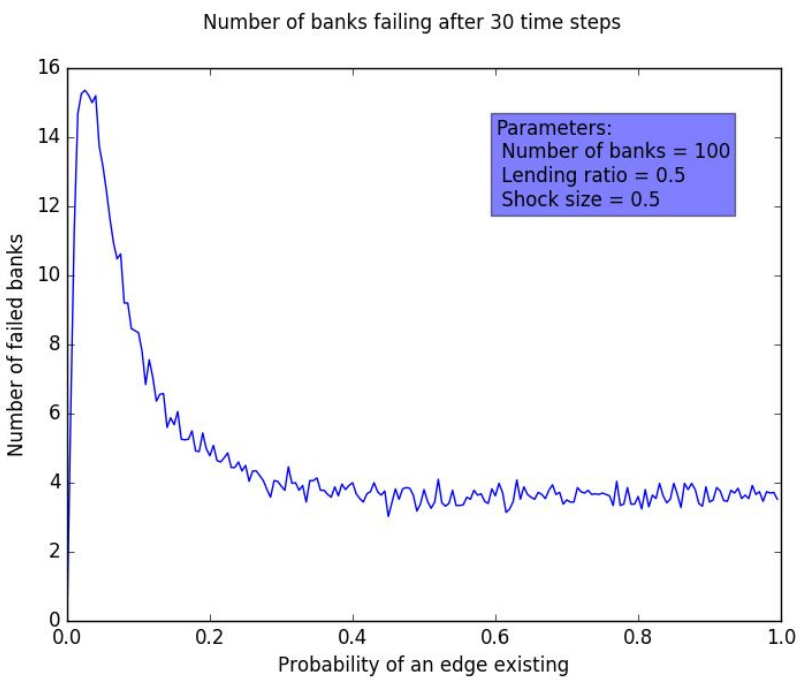
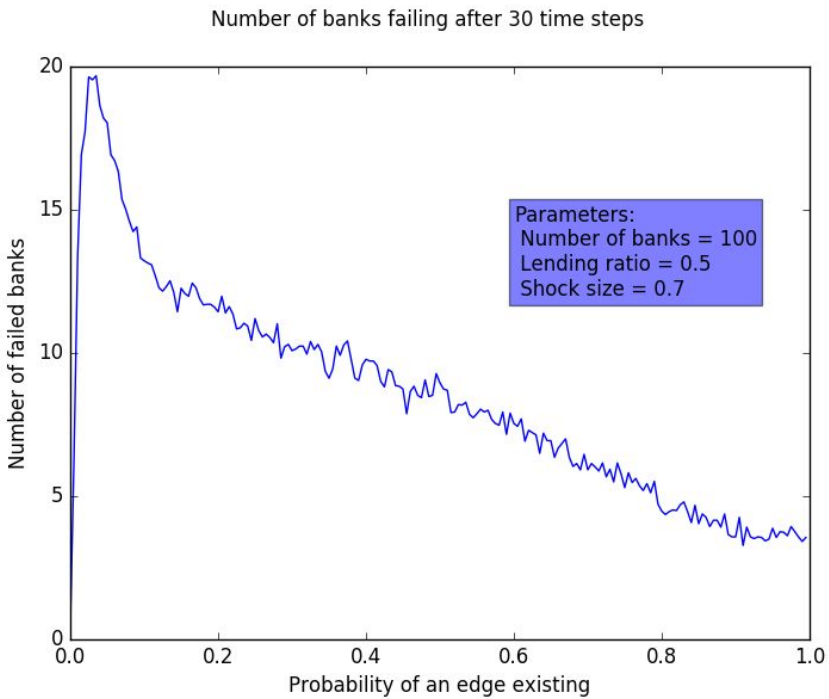
- The more banks lend out, the more they borrow as well, leading to a greater chance of an individual bank failing.
- Also, the fact that banks have lent out so much money to other banks make the secondary shocks more dangerous.

Varying the edge connection probability





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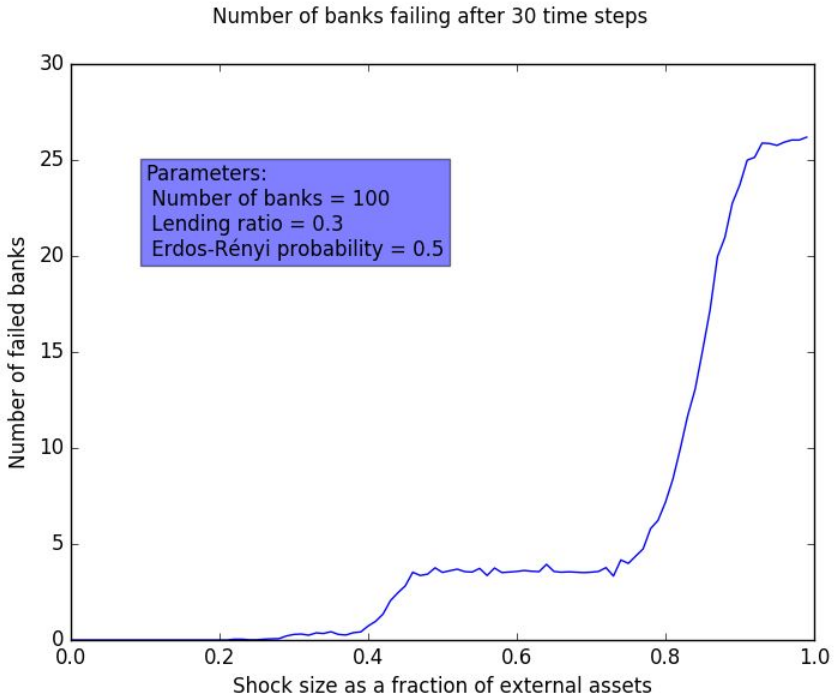
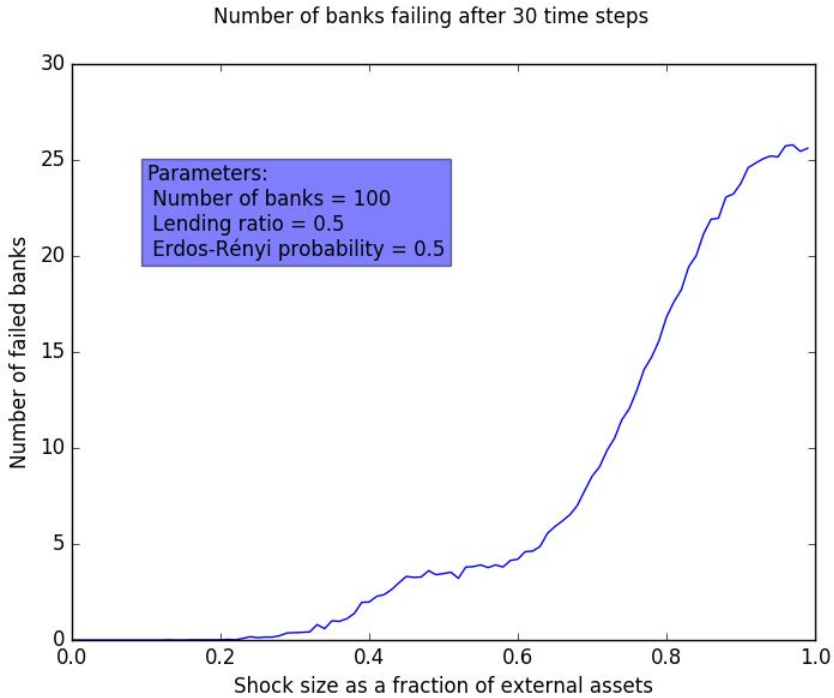
- It appears that a greater degree of interconnectivity is good for the system as a whole, even though it may be bad for an individual bank.
- Surprisingly, there's a peak at p=0.1, where the chance of the system collapsing is the highest. This probability stays consistent even when the other parameters are varied.

Varying the shock size





Varying the shock size (contd.)

- As can be seen from the graphs, the system can settle into one of three fixed states, depending on the shock size.
  - When the shock size is less than 0.4, then practically no banks fail in 30 time steps.
  - When the shock size is between 0.4 and 0.8, 5 out of 100 banks fail in 30 time steps.
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  - Beyond 0.8, the number of banks failing goes up drastically, with about 25 out of 100 banks failing.
- This observation can help us detect early signs of failure, and help us design mitigation measures.

Possible early warning signals

- One can look at time series data of banks' net worth, and by looking at the fluctuations, determine the mean shock size. If the shock size is beyond 0.8, that's a signal that the system will collapse with high probability in the next few time steps.

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- Another warning signal is the presence of low connectivity between banks. We've seen a low probability of an edge between two banks correlates with high risk of banks failing within the next few time steps.

Possible mitigation measures

- One way to mitigate the possibility of banks failing due to large shock sizes is to reduce the lending ratio of all the banks. This can be done centrally, i.e. the Reserve/Federal banks can mandate it for all banks. As we've seen, that reduces the risk of systemic failure.

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- Another way of mitigating risk would be to increase the connectivity between different banks. That can be done by encouraging them to lend and borrow money from various different banks, rather a few select banks.

Modelling ecosystems as graphs

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- The assets and liabilities can be seen as birth and death rate respectively, with the net worth being the overall growth rate. The net worth is then just growth rate, which if negative, kills off the population.

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- These fluctuations can correspond to the shock size in the InterBank model.
- That means if the shock size is beyond a certain threshold, the system will fail.
- This makes shock size an early warning signal.
- Unlike the InterBank model, we can’t affect the shock size in ecosystems we are only observing; we can only measure it. This means we can’t use it for mitigation strategies in those ecosystems.

Mitigating the possibility of a catastrophic shift

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- The challenge in mitigation is to expand the stability domain so that the system doesn’t undergo catastrophic transition.
- When we can control certain parameters in an ecosystem, e.g. fisheries, we can vary those parameters to ensure the system stays stable.

An example of a highly connected food web

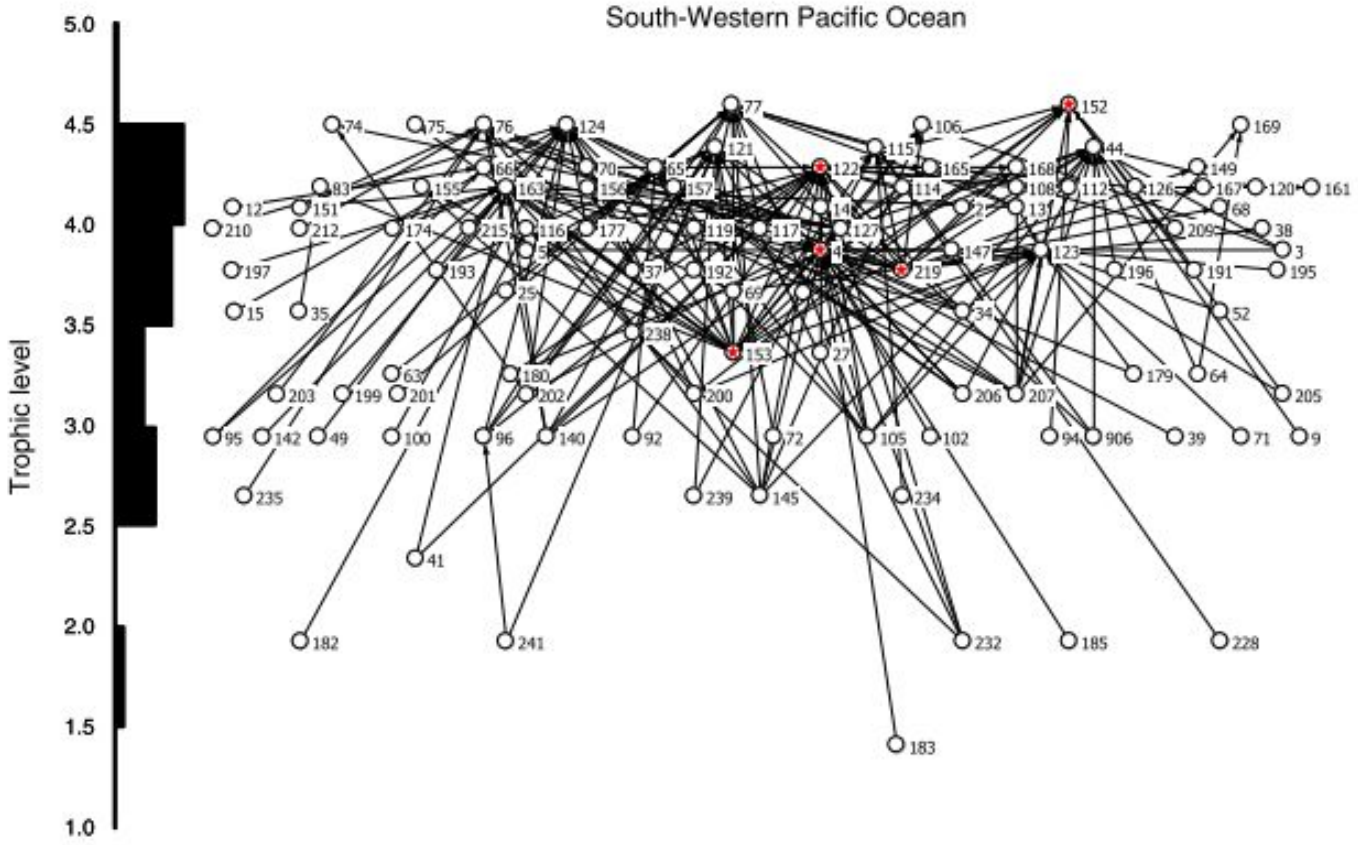

Image sourced from Progress in Oceanography, Dambacher et al.

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- The amount harvested by humans every season can be modelled analogous to the shock size in the InterBank model.
- As seen in the results of that model, the probability of a multiple banks failing goes up significantly if the shock size is more than a certain threshold.
- Similarly, the probability of multiple species going extinct in the ecosystem goes up significantly if the harvesting rate is beyond a certain threshold.

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- The InterBank model also doesn't account for the fact that banks may recover after an initial shock. The same also happens with ecosystems, i.e. they may recover after a shock.

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- This modelling technique revealed certain results about the system as a whole, something that wouldn’t have been possible if we focused on each individual separately.
- This modelling technique can be scaled up to include an arbitrary number of participants.
- The results obtained can be used to predict (with a certain probability of success) a failure in the future, and can also be used to design mitigation strategies.

References

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3. May and Pathy, Systemic Risk: the dynamics of model banking system (Primary reference)