Too interconnected to fail: Contagion and Systemic Risk in Financial Networks

Rama CONT

Joint work with:
Amal Moussa (Columbia University)
Andreea Minca (Université de Paris VI)
Edson Bastos (Banco Central do Brasil)

Financial stability and systemic risk

The recent financial crisis has simultaneously underlined the importance of contagion and systemic risk and the lack of adequate indicators for measuring and monitoring them.

Control over systemic risk has been the main motivation of the recent bailouts of large financial institutions

Regulators have had great difficulties anticipating the impact of defaults partly due to a lack of visibility and lack of relevant indicators on the structure of the financial system

Policy has been guided by “too big to fail” principle

Availability of better indicators of systemic risk would have helped outline a clearer regulatory and crisis management policy.

A need for indicators of systemic impact

- US Treasury has called “for new legislation granting additional tools to address systemically significant financial institutions” (Mar 2009).
- The new legislation ” would cover financial institutions that have the potential to pose systemic risks to our economy”.
- “In determining whether to use the program for an institution,Treasury may consider the extent to which destabilization of the institution could threaten the viability of creditors and counterparties exposed to the institution whether *directly* or *indirectly*.”
- What makes an institution systematically significant”?
- Need for indicators of systemic impact of the failure of a financial institution

OBJECTIVES

- A quantitative approach for measuring the systemic impact of the failure of a large financial institution: the Systemic Risk Index
- This index combines the effects of
  - common market factors affecting defaults
  - default contagion via counterparty risk
  - indirect contagion via credit default swaps
- use this measure of systemic risk on empirical data and simulated network structures to study the influence of counterparty exposures structure, credit default swaps and clearinghouses on systemic risk in the banking system.

Systemic vs marginal risk

- Bank regulation has focused on the risk of individual financial institutions (VaR) to determine capital requirements
- Capital should be sufficient to cover typical losses of large magnitude
- Value at Risk measures how much an institution can be harmed by market moves: it is concerned with the marginal loss distribution of its portfolio
- Systemic risk is concerned with how much the financial system can be harmed by the failure of the institution
- It is concerned with the joint distribution of the losses of all market participants and requires modeling how losses are transmitted through the financial system

LTCM

- Daily VaR= 400 million \$ in Aug 1998, Size= 4 billion\$.
- Amaranth: size = 9.5 billion USD.
- The default of Amaranth hardly made headlines: no systemic impact.
- The default of LTCM threatened the stability of the US banking system $\rightarrow$ Fed intervention
- Reason: LTCM had many counterparties in the world banking system, with large liabilities/exposures.
- **Point 1**: Systemic impact/ default contagion is not about the size of a firm
- **Point 2**: a firm's portfolio can be "well-hedged" (low market risk using conventional measures) but the firm can be a source of large systemic risk

The network approach to contagion modeling

We model a network of counterparty relations as a *weighted directed graph* where

- n vertices (nodes) $i \in V$ represent financial market participants: banks, funds, corporate borrowers and lenders, hedge funds, insurers, monolines.
- (directed) links represent counterparty exposures: L_{ij} is the the (market) value of liabilities of i towards j, L_{ji} is the exposure of i to j.
- In a market-based framework L_{ji} is understood as the fair market value of the exposure of i to j.
- Each institution i disposes of a *capital buffer* c_i for absorbing market losses. Proxy for c_i: Tier I+II capital minus required capital for non-banking assets.

- Solvency condition: $c_i + \sum_j L_{ji} - \sum_j L_{ij} > 0$
- Capital absorbs first losses. Default occurs if Loss(i)$> c_i$.

Assets	Liabilities
Interbank assets $\sum_j L_{ji}$	Interbank liabilities $\sum_j L_{ij}$
Other assets A_i	Capital C_i

Table 1: Stylized balance sheet of a bank.

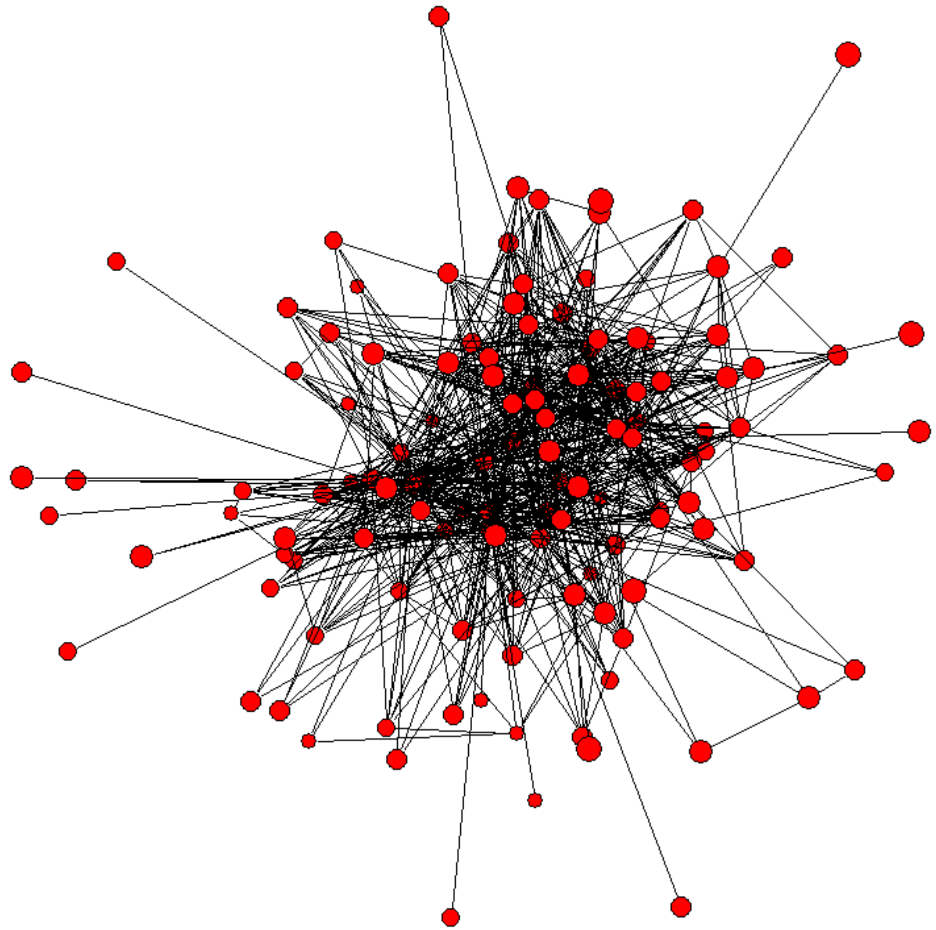

Figure 1: Brazilian interbank network (Cont & Bastos 2009).

Contagion in banking networks: theory

Humphrey (1987) Allen & Gale (2000) Kiyotaki & Moore
Rochet & Tirole (1996) Freixas et al (1997) Nier et al (2007)...

Theoretical results on the influence of network structure on contagion have been obtained only for a limited number of highly stylized structures of interbank markets, chosen more for analytical convenience than for their resemblance to real world banking systems.

These studies suggest however that the magnitude of contagion depends on

the size of interbank exposures relative to capital

the precise pattern of such linkages (network structure).

Contagion in banking networks: empirical studies

Empirical studies on interbank networks by central banks:

- Sheldon and Maurer (1998) for Switzerland
- Furfine (1999) for the US
- Upper and Worms (2000) for Germany Wells (2002) for the UK
- Boss, Elsinger, Summer and Thurner (2003) for Austria
- Mistrulli (2007): Italy
- DeGryse & Nguyen : Belgium, Soramaki et al (2007): Finland

examine by simulation the impact of single or multiple defaults on bank solvency in absence of other effects (e.g. market shocks).

Mostly focused on payment systems (FedWire, etc)

The small magnitude of such "domino" effects has been cited as justification for ignoring contagion e.g. in the Geneva Report.

Such simulation ignore the impact of correlated market shocks on bank balance sheets.

Many studies on domino effects are not based on actual exposures but *estimate* exposures from balance sheet data using maximum entropy methods (Boss et el, Elisgner et al) which result in distributing as uniformly as possible liabilities among counterparties. This method can lead to underestimation of contagion effects.

- “Market clearing equilibrium” (Eisenberg & Noe (2001) Elsinger et al (2005)) amounts to computing cash flows assuming simultaneous liquidation of all market participants positions. Defaults are then generated endogenously.

  Not a realistic situation: defaults are not generated by global market clearing but may appear as exogenous shocks to capital reserves of banks.

- Portfolio approach (Lehar 2005, Elsinger et al 05): consider the financial system as a portfolio, simulate its loss distribution and compute a risk measure (Value at Risk) for this “portfolio”.

  Such global measures do not isolate the impact of a single default or compute the systemic impact of a given institution.

- Finally, these studies have ignored the impact of credit risk transfer instruments such as credit default swaps on systemic risk.

Brazil's banking system: a directed scale-free network

Joint work with Edson BASTOS, Banco Central do Brasil.

- Data set of all consolidated interbank exposures (incl. swaps)+ Tier I and Tier II capital (2007-08).
- $n \simeq 100$ institutions (holdings), $\simeq 1000$ counterparty relations
- Average number of counterparties (degree)$= 7$
- Heterogeneity of connectivities: in-degree (number of debtors) and out-degree (number of creditors) have Pareto distributions with exponents $\alpha_{in}, \alpha_{out}$ between 2 and 3.
- Exposure sizes very heterogeneous: heavy tailed Pareto distribution with exponent between 2 and 3.
- These distributions are stable across time

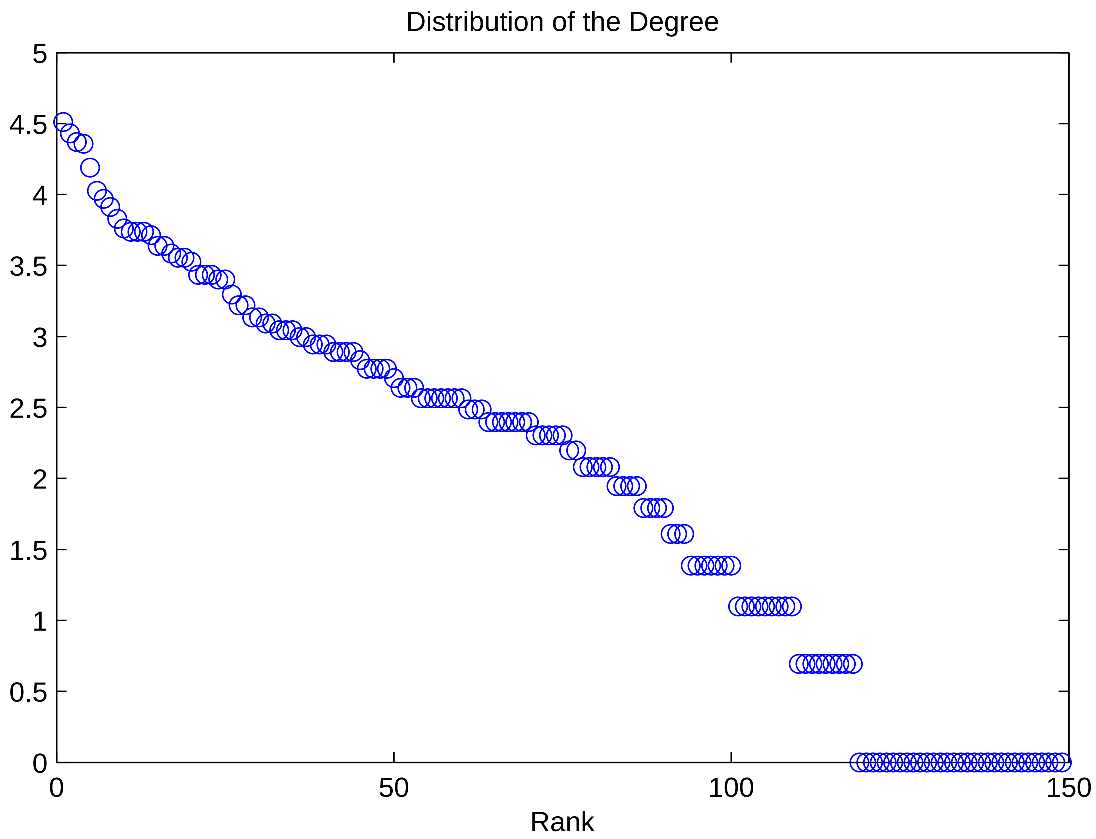

Figure 2: Brazilian interbank network: distribution of degree (number of counterparties).

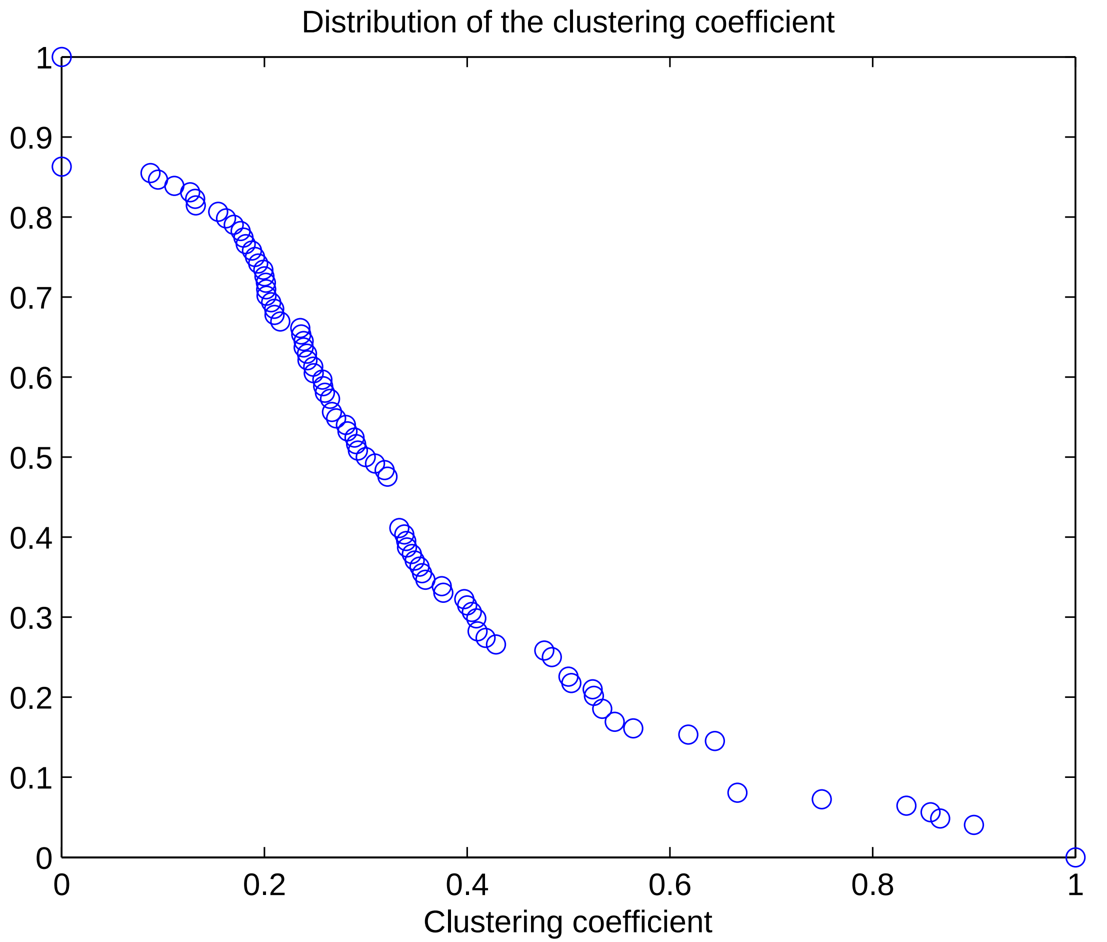

Figure 3: Brazilian interbank network: distribution of clustering coefficient

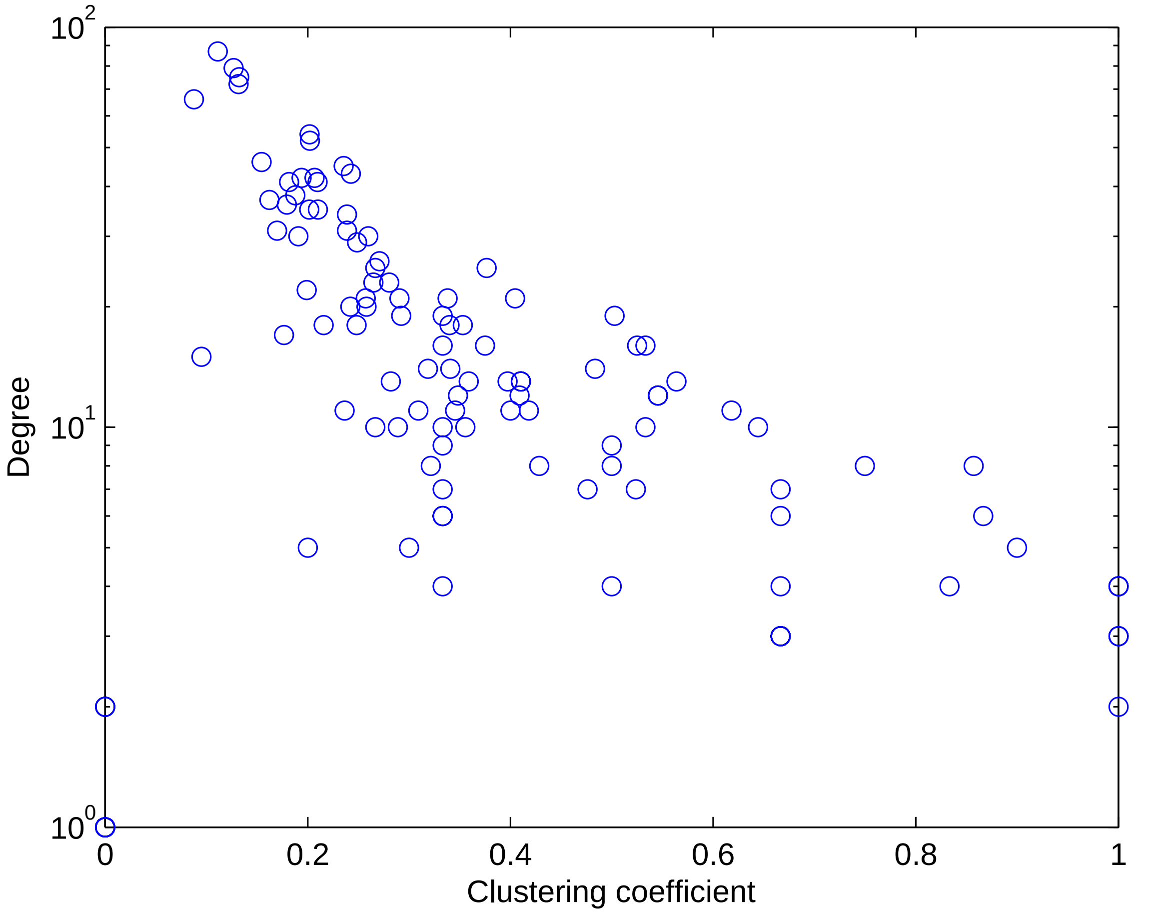

Figure 4: Brazilian interbank network: degree vs clustering coefficient.

Network formation by preferential attachment

Graphs with Pareto/ power-law degree distributions, called **scale-free networks**, are observed to emerge in various applications, most notably the structure of the Internet and social networks (Albert and Barabasi 2002, Bollobas Borgs, Chayes, Riordan 2003)

The presence of such power laws can be explained in terms of a *preferential attachment* model for counterparty choice.

The idea is that a new firm entering the financial system is more likely to establish financial links with highly connected firms.

A directed scale-free network model

Each time a new node v is added,

- with probability $1/2 > p > 0$, add a link from v to an existing vertex w chosen with probability

$$\frac{deg_{\text{in}}(w) + \delta_{\text{in}}}{\sum_{i=1}^{|G(t)|}(deg_{\text{in}}(i) + \delta_{\text{in}})}. \tag{1}$$

- With probability p, add a link from an existing vertex w to v, where w is chosen with probability

$$\frac{deg_{\text{out}}(w) + \delta_{\text{out}}}{\sum_{i=1}^{|G(t)|}(deg_{\text{out}}(i) + \delta_{\text{out}})}. \tag{2}$$

- With probability $1 - 2p$, link an existing vertex w_1 to an existing vertex w_2, where w_1, w_2 are chosen independently, w_1 with probability (2) and w_2 with probability (1).

- Allocate a random exposure to each link.

Property 1 (Degree distributions)**.** *As $N \to \infty$ the proportion of nodes with in (rnesp. out)-degree k converges to a distribution $q_{\text{in}}(k)$ (resp. $q_{\text{out}}(k)$) with Pareto tails:*

$$\frac{1}{N}\#\{v \in [G_N], indeg(v) = k\} \overset{N\to\infty}{\to} q_{\text{in}}(k) \quad a.s. \tag{3}$$

$$\frac{1}{N}\#\{v \in [G_N], outdeg(v) = k\} \overset{N\to\infty}{\to} q_{\text{out}}(k) \quad a.s. \tag{4}$$

$$\text{where} \qquad q_{\text{in}}(k) \overset{k\to\infty}{\sim} \frac{C_{\text{in}}}{k^{\alpha_{\text{in}}}} \qquad q_{\text{out}}(k) \overset{k\to\infty}{\sim} \frac{C_{\text{out}}}{k^{\alpha_{\text{out}}}} \tag{5}$$

$$\text{with} \qquad \alpha_{\text{in}} = \frac{2 - p + 2p\delta_{\text{in}}}{1-p} \qquad \alpha_{\text{out}} = \frac{2 - p + 2p\delta_{\text{out}}}{1-p} \tag{6}$$

Example: $p = 0.1, \delta_{in} = 0, \delta_{out} = 4.45$ yields the tail exponents

$$\alpha_{\text{in}} = 2.1 \qquad \alpha_{\text{out}} = 3.1$$

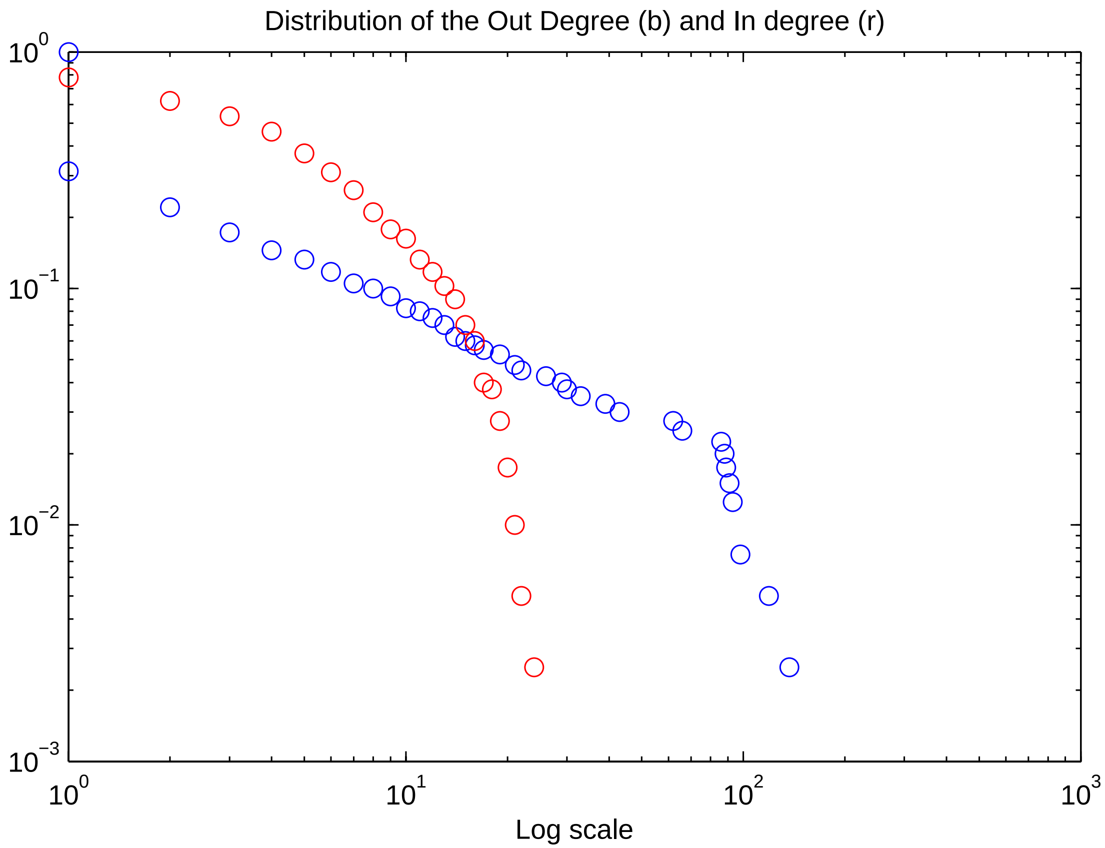

Figure 5: Degree distributions obtained for random attachment model. In-exponent: 2.1; Out-exponent: 3

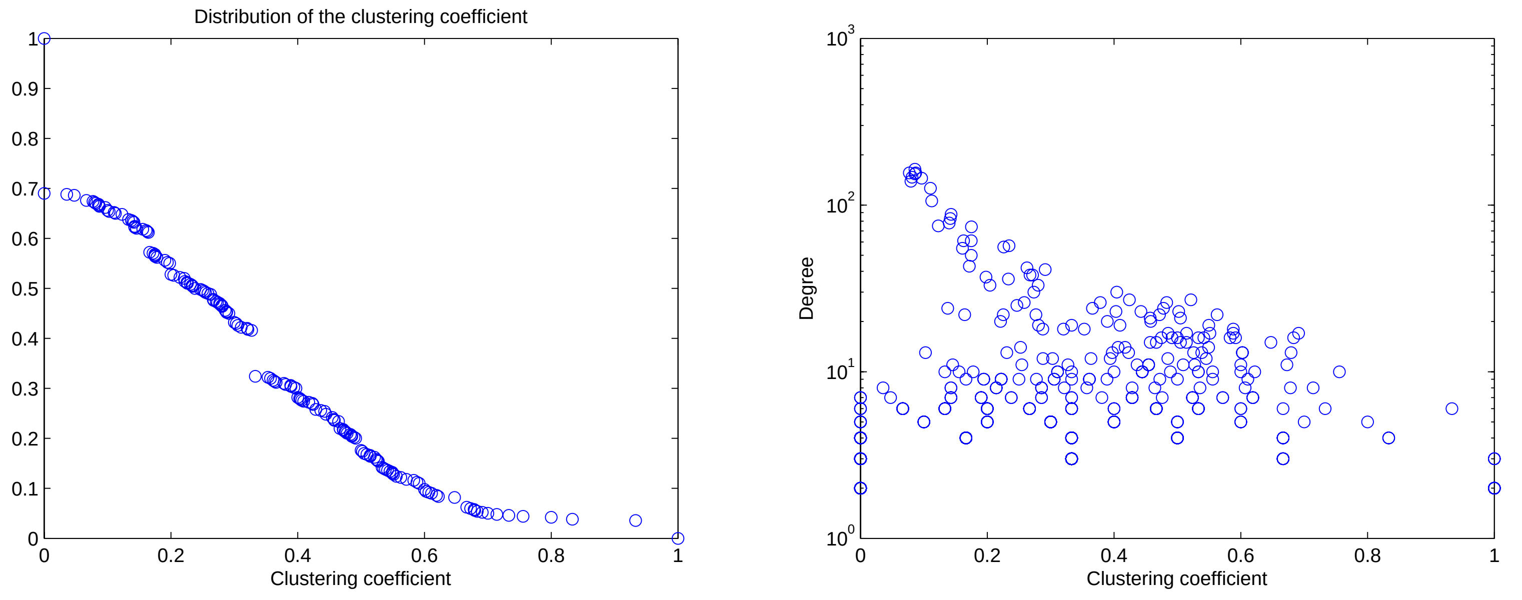

Figure 6: Left: distribution of clustering coefficient. Right: clustering coefficient vs degree.

Measuring the systemic impact of a default

Objective: quantify the losses generated across the network by the initial default of a given financial institution.

We consider two mechanisms which contribute to contagion in the network:

1. default contagion across counterparty networks
2. correlated, market shocks

Mechanism 1: market-induced credit event

If a bank i faces unexpected market loss (e.g. writedown of assets resulting from large sudden market moves), it can default if the loss exceeds its capital c_i

Such losses can arise from

- Exogenous market shocks: this is modeled by applying correlated shocks ϵ_i across balance sheets

$$c_i \mapsto \max(c_i + \epsilon_i, 0)$$

- Margin calls or payments on bilateral contracts to another market participant j ex. credit default swaps triggered by credit events in the network.

$$c_i \mapsto \max(c_i - \Pi_{ij}, 0)$$

Mechanism 2: contagion via counterparty risk

The default of a market participant i affects its counterparties in the following way over a short term horizon

- Debts are collected from debtors at liquidation:

$$\forall j, L_{ji} \to 0$$

- Creditors loses a fraction $(1 - R)$ of their exposure.
Loss is first absorbed by capital: $c_j \to \min(c_j - (1 - R)L_{ij}, 0)$.
This leads to a writedown of $(1 - R)L_{ij}$ in the balance sheet of j, which can lead to **default**/ credit event for j if

$$c_j < (1 - R)L_{ij}$$

Typically recovery $R \simeq 0$ in the short term.

Default cascades

Default of a market participant i incurs losses to its counterparties. These losses may lead the counterparties to default and generate a "cascade" of defaults.

Definition 1 (Default cascade). *Given exposures* (L_{ij}), *capital buffers* (c_i), *and recovery rates* (R_i), *we define a sequence*

$$D_0^A \subset D_1^A \subset \cdots \subset D_n^A$$

of defaults generated by the initial default of a subset $A \subset V$ *of nodes via:*

$$D_0^A = A \qquad \forall k \geq 1,\ D_k^A = \{i \ s.t.\ c_i < \sum_{j \in N_i^+ \bigcap D_{k-1}^A} (1 - R_j) L_{ji}\} \quad (7)$$

This sequence is called the **default cascade** *generated by* A.

Contagion stops at round $\tau(A)$ when counterparties can bear the losses and no more defaults occur

$$\tau(A) = \inf\{t \geq 0,\ D_t^A = D_{t-1}^A\} \leq N$$

$\tau(A)$ is the length of the cascade generated by the initial defaults A.

Default Impact

We define the "default impact" $DI(A)$ of a group A of institutions as the total loss (in $) in the default cascade generated by the initial default of all institutions in A.

Definition 2. *The Default Impact $DI(A)$ of a set $A \subset V$ of nodes is the total loss to the financial system along the cascade generated by initial default of all nodes in A:*

$$DI(A) = \sum_{i \in D^A_{\tau(A)}} (c_i + \sum_{i \in V \setminus D^A_\tau} L_{ij})$$

The default impact of an institution $i \in I$ is defined as $DI(i) = DI(\{i\})$.

$DI(i)$ is a worst-case loss estimate and does not involve estimating the default probability of i.

Analogy w/ "Influence functions" in social networks.

Default contagion during a crisis: combining market risk and contagion effects

Default contagion during a crisis: evaluate impact of a large default in presence of (correlated shocks) to capital structure across institutions

1. Network structure $(c(0), L)$ is given at $t = 0$
2. Market risk of bank portfolios is simulated using a factor model: (correlated) downward shocks are applied to balance sheets of different institutions

$$c_j(T) = c_j(0) + \epsilon_i \qquad (\epsilon_i, i \in I) \sim F$$

3. We now consider default of i and compute the Default Impact $DI(i)$ in the "stressed market" environment characterized by $(c(T), L)$
   $DI(i)$ is now a random variable depending on $c(T)$.

Ex: Gaussian one-factor model $\epsilon_i(T)$

$$c_i(T) = F_i^{-1}(N(X_i)) \qquad X_i = (\sqrt{\rho} Z_0 + \sqrt{1-\rho} Z_i)$$

where Z_i are IID N(0,1).

Ex: a heavy-tailed factor model $\epsilon_i(T)$

$$c_i(T) = F_i^{-1}(G_i(X_i)) \qquad X_i = (\sqrt{\rho} Z_0 + \sqrt{1-\rho} Z_i)$$

where Z_i are α-stable with $\alpha = 1$.

Lehar (2005) gives estimates for volatilities and correlations of assets of international banks: $\rho \in [0.2, 0.6]$.

More generally one can use other factor model commonly used in portfolio default risk simulations.

Systemic Risk Index of a financial institution

We now combine the

(deterministic) computation of Default Impact and the

(stochastic) simulation of correlated defaults at horizon T and define the Systemic Risk Index of the institution i at a horizon T as

$$S(i) = E[DI(i)|c_i(T) \leq 0]$$

It is the expected loss in the cascade generated by the failure of i, given that at the time of failure the capital buffer of i has been wiped out by market shocks.

This indicator combines market-based measures of default probability and correlation/dependence with a network-based measure of default contagion.

Systemic Risk index as a risk measure

Similarly we can define the Systemic risk contribution of a set $A \subset V$ of financial institutions: it is the expected loss to the financial systems generated by the joint default of all institutions in A:

$$S(A) = E[DI(A) | \forall i \in A, c_i(T) \leq 0]$$

S then defines a set function

$$S : \mathcal{P}(V) \mapsto \mathbb{R}$$

The Systemic Risk Index can be viewed, from the point of view of the *regulator*, as a macro-level "risk measure".

Simulation experiments

We generate a directed scale-free network with $n = 400$ nodes with Pareto distributions for degree and exposure sizes which match the empirical properties of Brazilian and Austrian networks.

- Heterogeneity of connectivities: in/ out-degree has Pareto distribution with exponents 2.1 and 3.
- Exposures L_{ij} are IID with a Student distribution with $\nu = 1.9$ degrees of freedom ($\rightarrow$ Pareto tail)

We consider two different situations for the capital:

- Limit on leverage: $c_i \geq \alpha \sum_j L_{ij}$ where $\alpha =$ minimal capital ratio
- Capital computed according to Basel II rules: may allows for large/unlimited leverage

Default impact is computed for each node.

Systemic risk index is computed by Monte Carlo using an importance sampling method for efficiently sampling joint default events

To quantify the impact of imposing a maximal leverage ratio *without increasing total amount of available capital reserves* we conduct an experiment where the the ratio is fixed in a way that the total amount of capital reserves summed across institutions is the same in both cases.

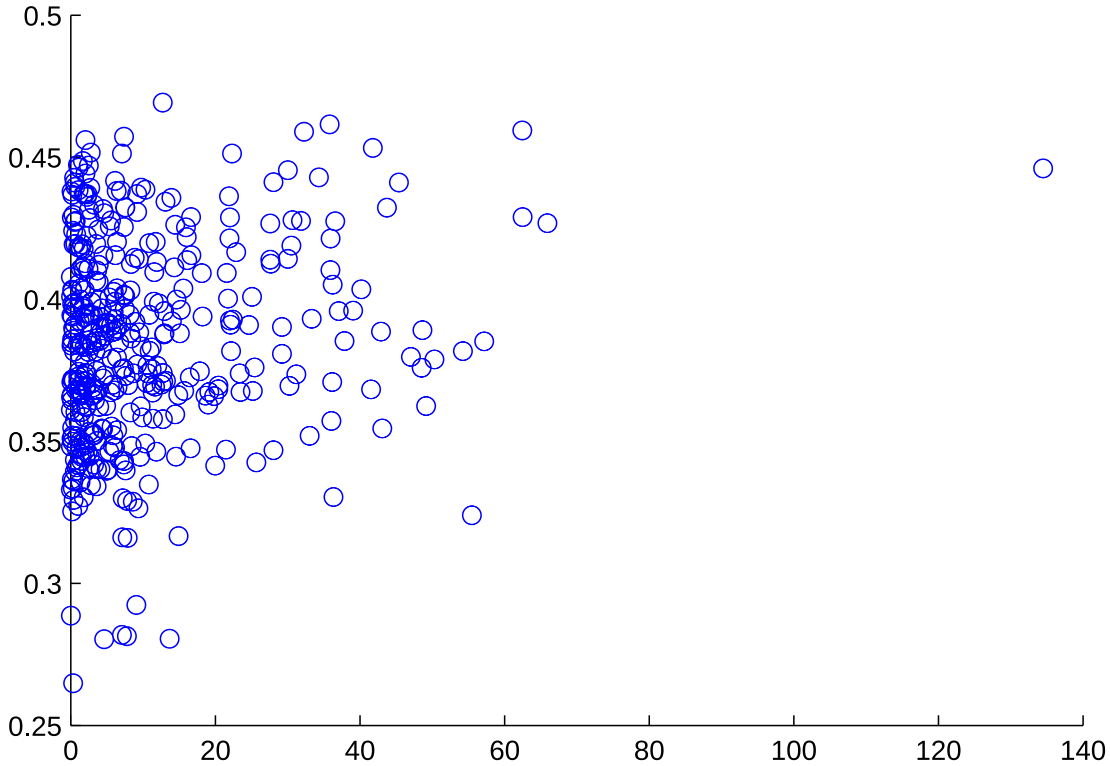

Figure 7: ‘Too big to fail”? Systemic risk index vs size.

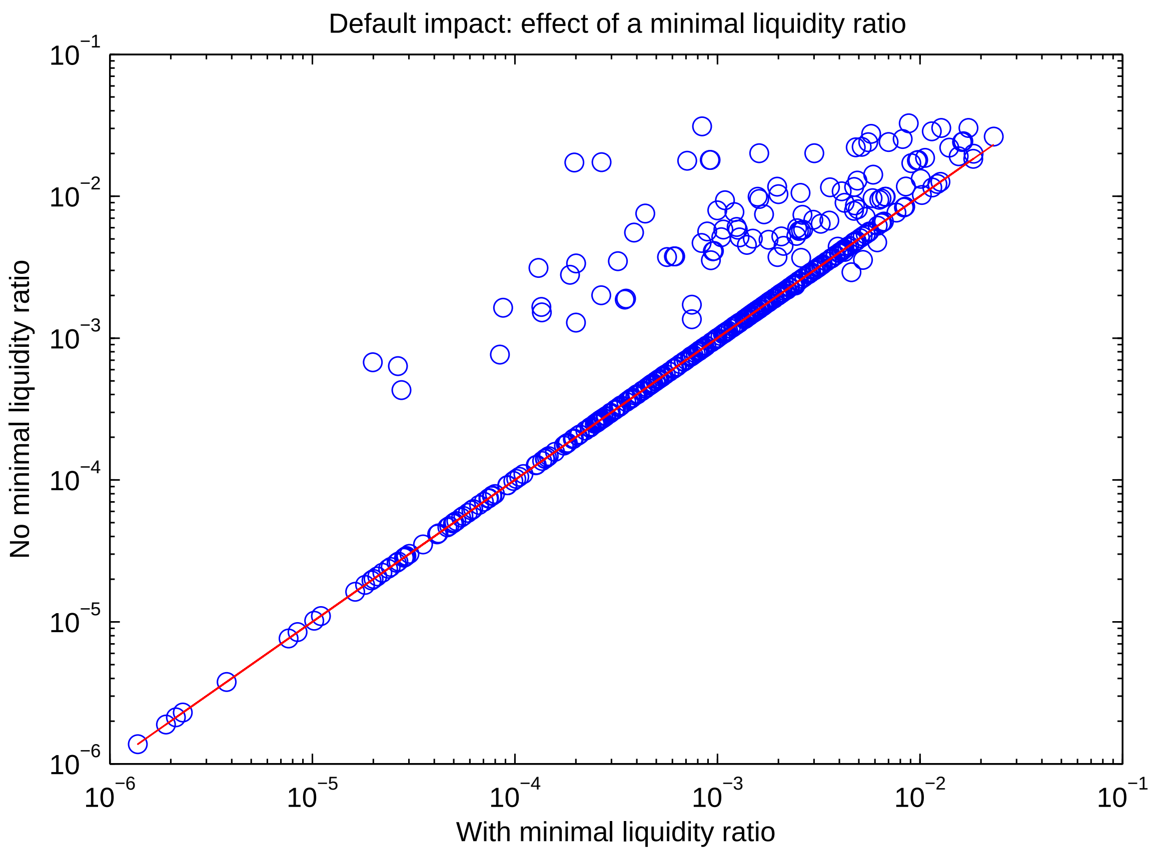

Figure 8: Influence of leverage regulation on default impact: **imposing a cap on leverage reduces contagion**.

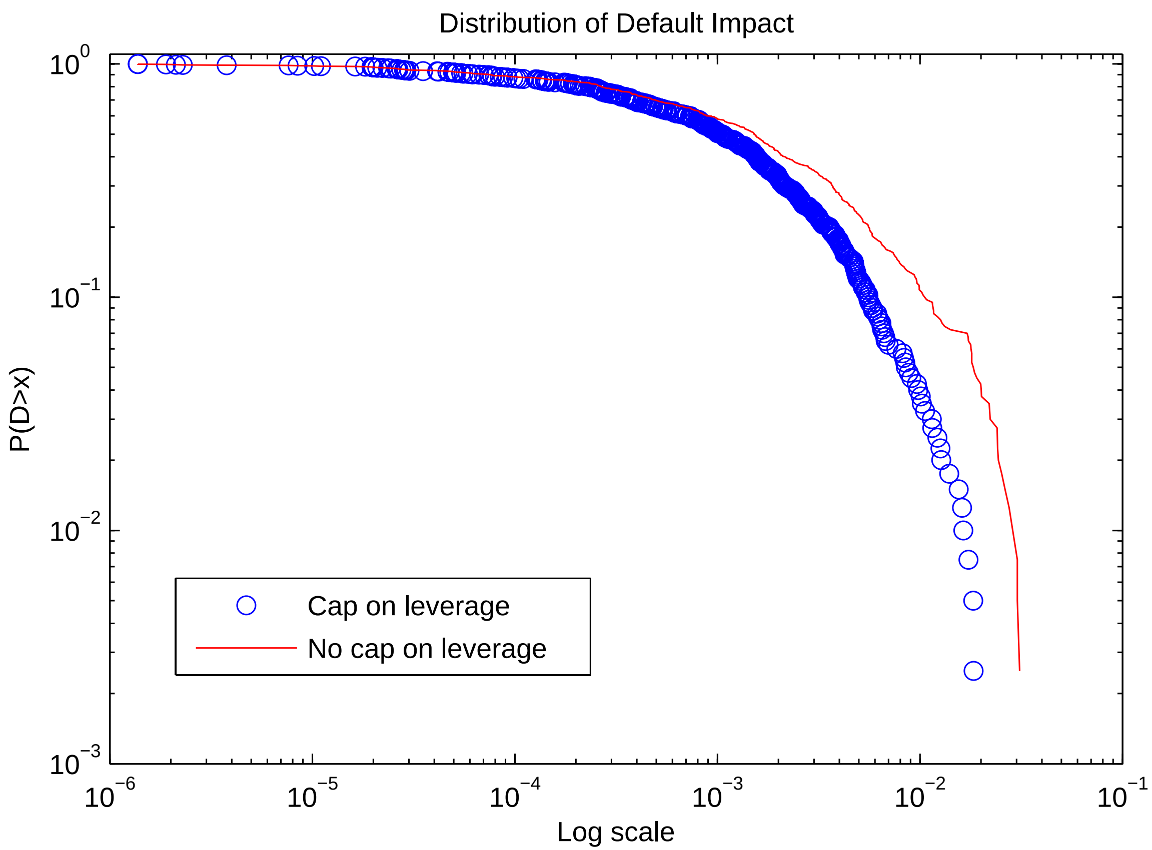

Figure 9: Influence of leverage regulation on default impact: **imposing a cap on leverage reduces proportion of institutions with large default impact.**

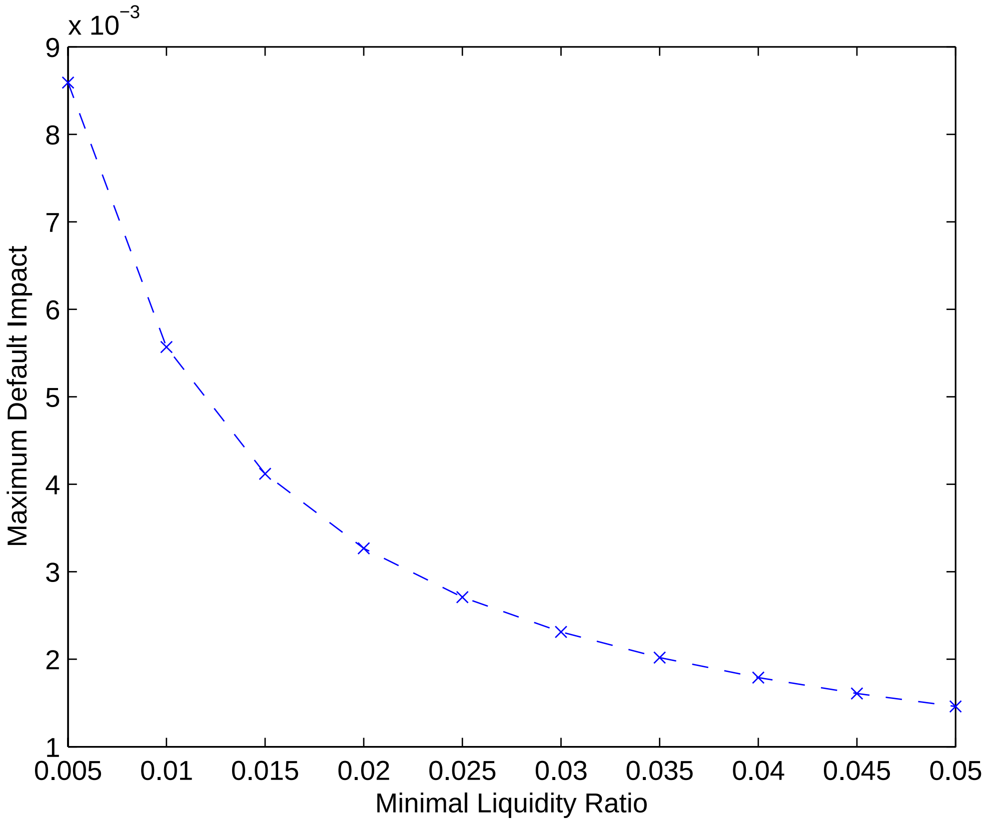

Figure 10: **Imposing a cap on leverage reduces default impact of systemically important institutions**: Loss generated by the institution with highest default impact as a function of the minimal ratio of capital to total exposures.

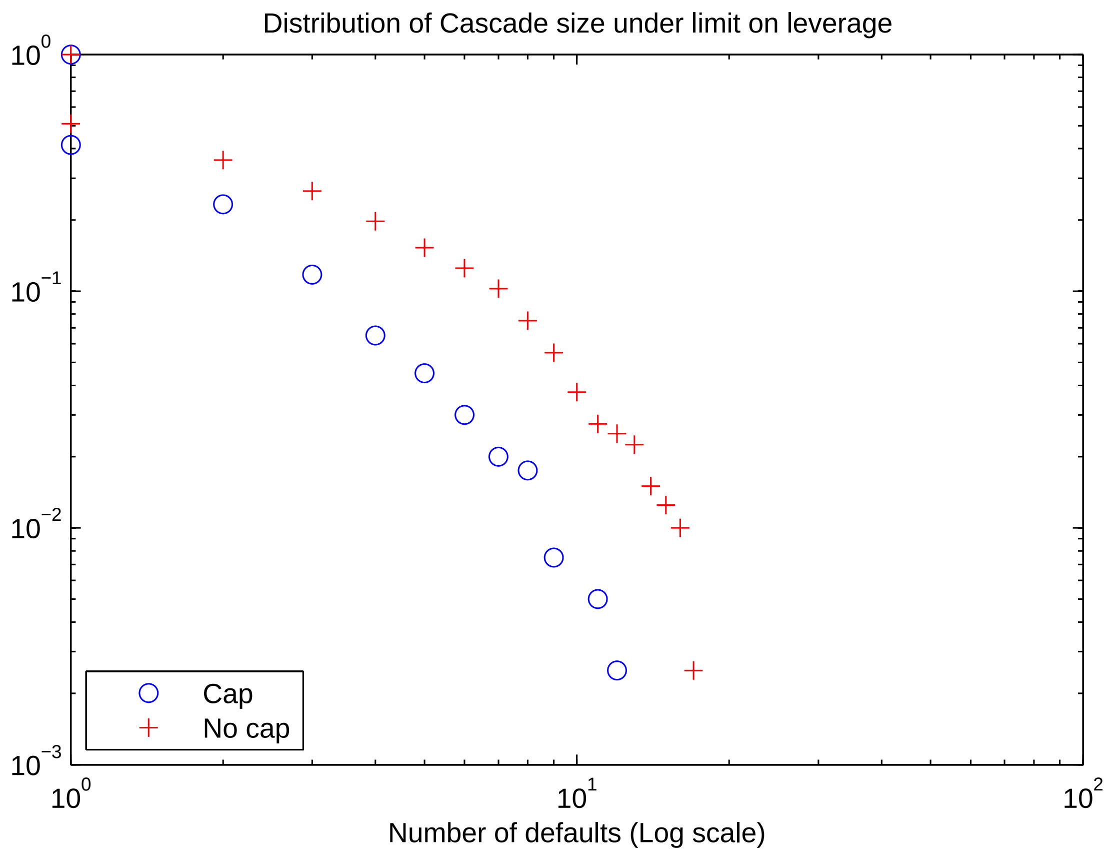

Figure 11: Distribution of number of defaults generated in a cascade: **imposing a cap on leverage reduces contagion**.

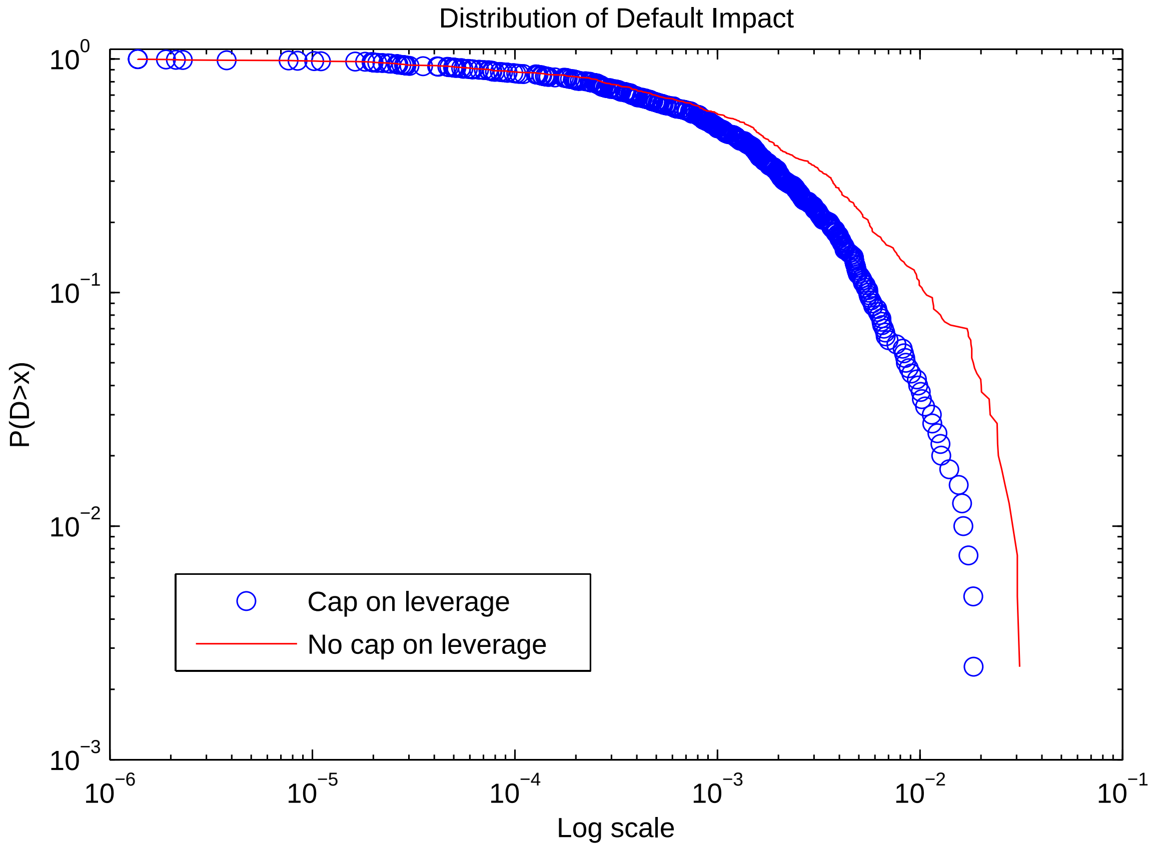

Figure 12: Influence of leverage regulation on distribution of default impact: **imposing a cap on leverage reduces probability of large systemic losses.**

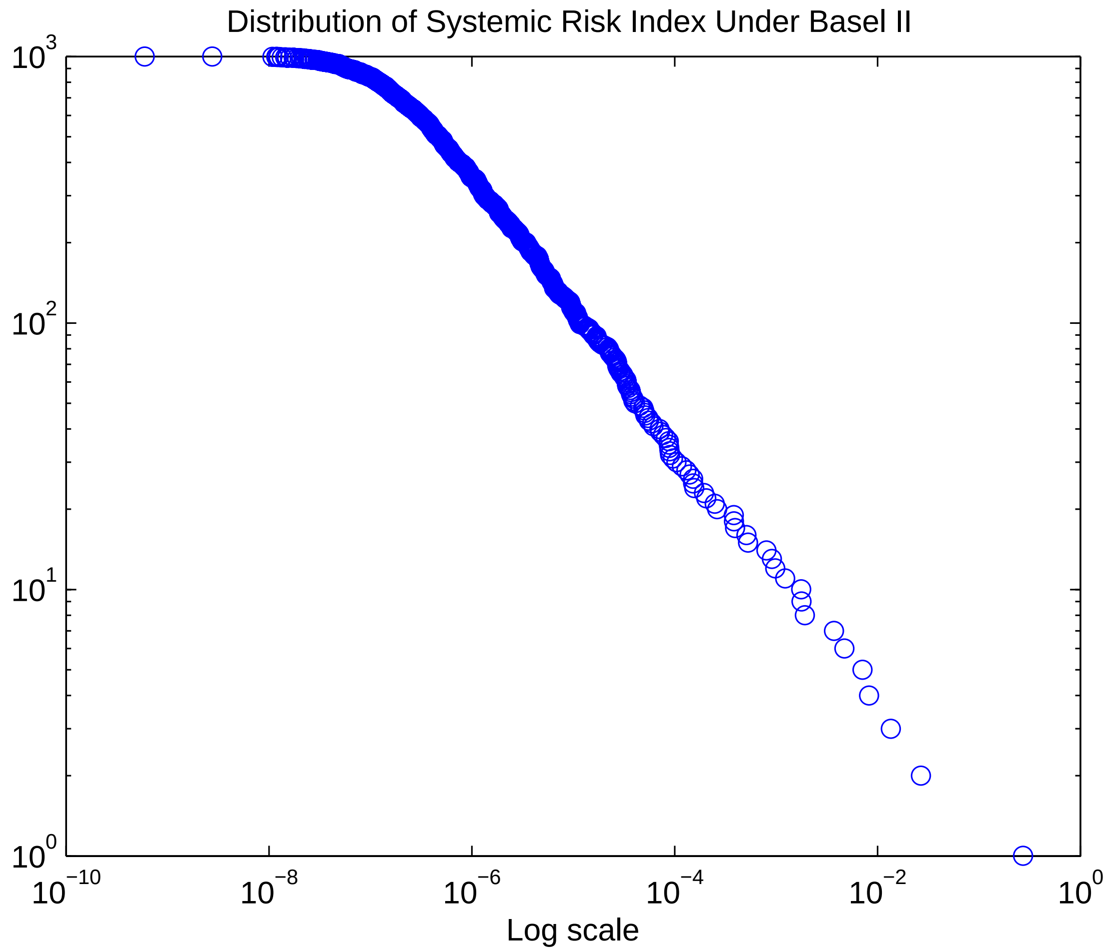

Figure 13: Distribution of systemic risk index: no cap on leverage.

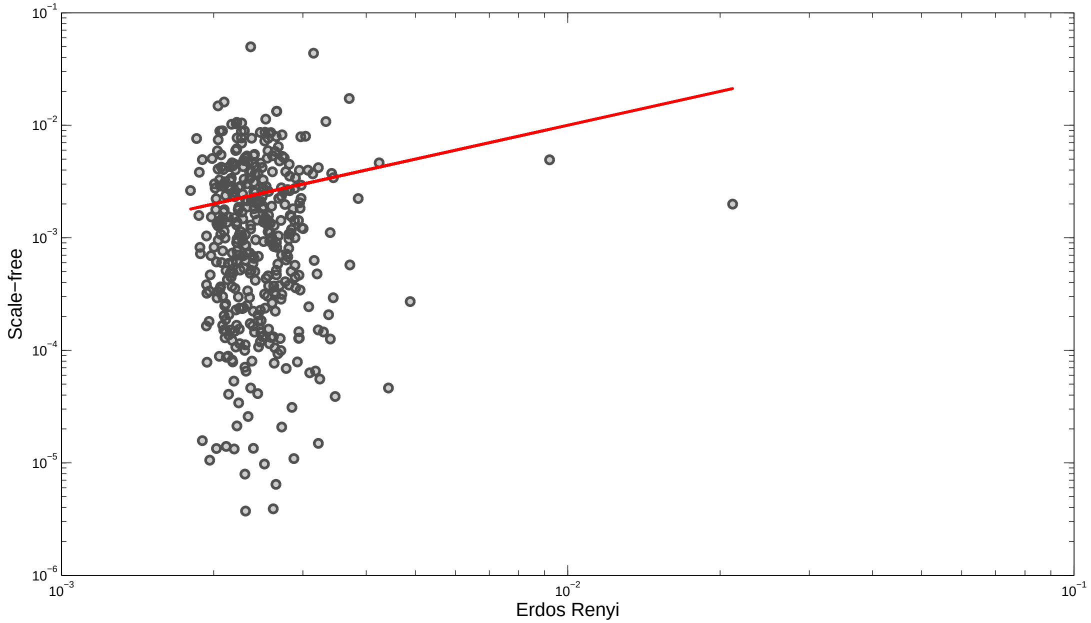

Figure 14: Influence of network structure on systemic risk: Erdös-Renyi random graph vs scale-free network.

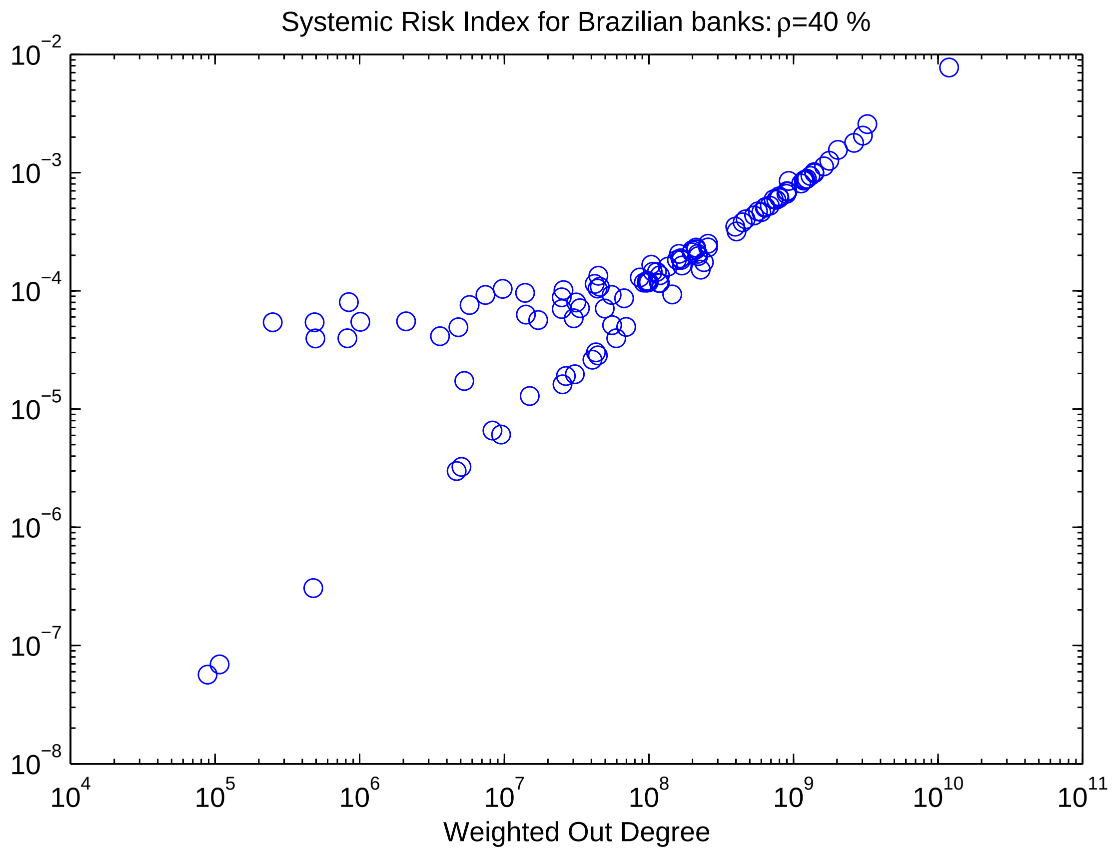

Figure 15: Systemic risk index vs total liabilities: evidence of contagion in Brazil interbank network.

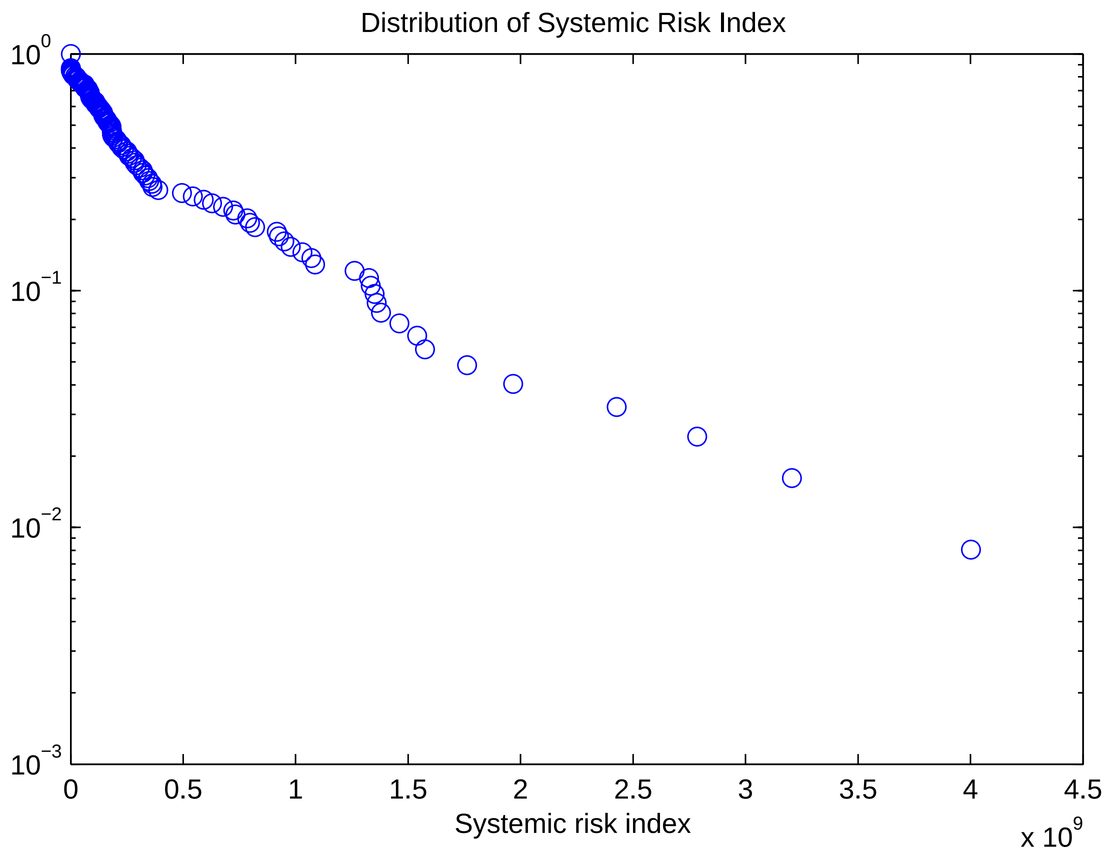

Figure 16: Distribution of systemic risk index: Brazil interbank network.

What makes a node systemically important?

Node	Systemic risk index	In degree	Out degree	Weighted in degree	Weighted out degree	Leverage
13	0.18	6	8	47.90 10^7	2327.0 10^7	4.05
108	0.15	0	5	0	0.13 10^7	0
30	0.12	22	28	117.29 10^7	1123.5 10^7	0.12
37	0.09	2	1	0.86 10^7	0.86 10^7	0.08
117	0.07	0	1	0	0.30 10^7	0
Network	0.06	8.56	8.56	6.07 10^8	6.07 10^8	0.81

Table 2: Analysis of the five institutions with highest systemic risk index: Brazilian banking system.

Covariate	**Coefficient**	**Standard Error**	**p-value**
$\max(SI^{\mathcal{N}})$	**-0.0563**	**0.0406**	**0.1661**
$\max(leverage^{\mathcal{N}})$	**0.0012**	**0.0053**	**0.8231**
$\max(SI^{\mathcal{N}} * leverage^{\mathcal{N}})$	**0.0084**	**0.5599**	
$outdegree$	**0.0027**	**0.0089**	**0.7568**
$outdegree * max(SI^{\mathcal{N}})$	**0.0143**	**0.0015**	**4.5e-19**
$\max(weightedoutdegree^{\mathcal{N}})$	**1.3 e-4**	**3.2e-4**	**0.68**

Table 3: Stepwise regression selects outdegree$\times$ $\max(SI^{\mathcal{N}})$ where SI^N is the systemic risk index for the counterparties) as the most significant variable. Not only the connectivity (out degree) matters but also the systemic risk index of its neighbors.

The systemic impact of an institution is **not** posssible to determine just given that institutions aggregate portfolio risk (VaR etc.). It depends primarily on its counterparties, exposure to counterparties, their degree of leverage etc: i.e. its **environment in the network**. Good indicator of the degree of systemic importance of a financial institution seems to be

$$\max_j \frac{L_{ij}}{c_j} = \max_{\text{Counterparties exposed to i}} \frac{\text{Exposure of j to i}}{Capital\ buffer\ of\ j}$$

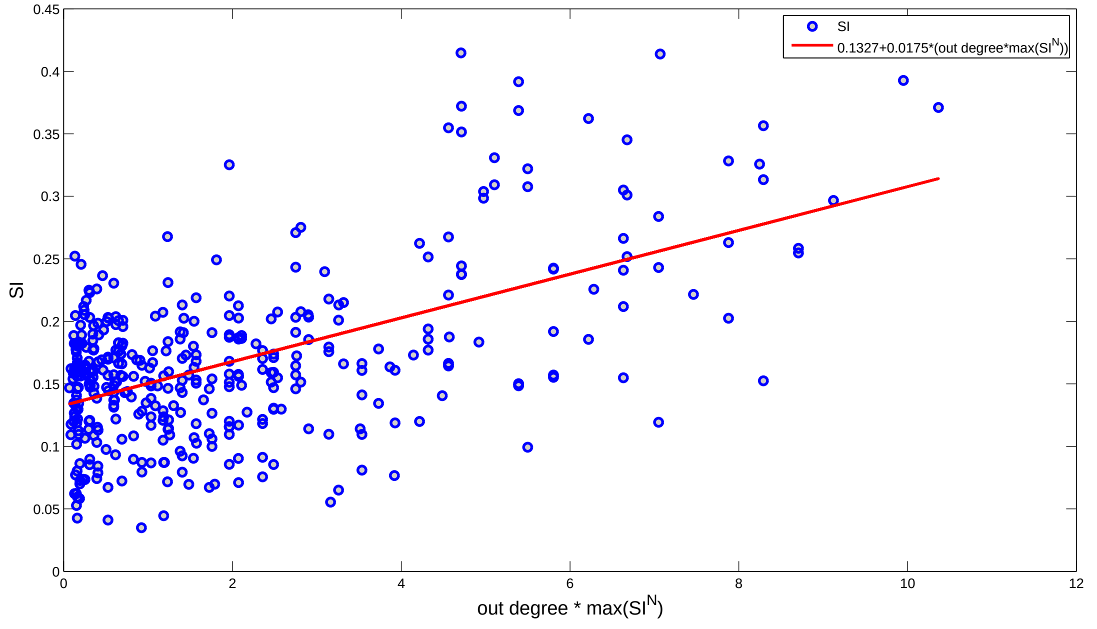

Figure 17: Systemic risk index versus (out degree * Maximum Systemic risk index among counterparties)

Analysis of cascades in large networks

We describe the topology of a large network by the joint distribution $\mu_n(j,k)$ of in/out degrees and assume that μ_n has a limit μ when graph size increases in the following sense:

1. $\mu_n(j,k) \to \mu(j,k)$ as $n \to \infty$: the proportion of vertices of in-degree j and out-degree k tends to $\mu(j,k)$).
2. $\sum_{j,k} j\mu(j,k) = \sum_{j,k} k\mu(j,k) =: m \in (0,\infty)$ (finite expectation property);
3. $m(n)/n \to m$ as $n \to \infty$ (the average degree tends to m).

A criterion for robustness with respect to contagion

We call a node **fragile** if either prone to default if either **one** or **two** of their counterparties default: its capital buffer is lower than the sum of the two largest exposures.

Let $q(d_+, d_-)$ be the proportion of **fragile** nodes in the network with in-degree d_+ and out-degree d_-. This quantity is empirically accessible to the regulator.

Proposition 1 (Amini, Cont, Minca 2009)**.** *If*

$$E[\text{Degree}] < E^{\mu}[d_+(i)d_-(i)\ q(d_+(i), d_-(i))] \tag{8}$$

the default of a single node can trigger a cascade default of a positive fraction of the financial system.

If

$$E[\text{Degree}] > E^{\mu}[d_+(i)d_-(i)\ q(d_+(i), d_-(i))] \tag{R}$$

the cascade generated by any finite set of initial defaults remains contained: its size is $o(n)$ as $n \to \infty$.

E[.] denotes here the expectation with respect to the joint distribution $\mu(d_+, d_-)$ of in-/out-degrees in the large network.

Robustness condition:

$$\text{Average degree} > \frac{1}{n}\sum_i [d_+(i)d_-(i)\ q(d_+(i), d_-(i))] \tag{9}$$

Credit Default swaps

- Credit default swaps are (off balance sheet) OTC contracts involving A selling protection to B on default of C.
- Upon default of C, A has to pay to B the loss given default, proportional to the notional of the CDS contract.
- June 2008: total interbank assets totaled $\simeq$ 39 trillion USD in June 2008
  Notional amount of single name credit default swaps = 38 trillion USD.
- If B already has exposure to C then the CDS has the effect of *replacing* the exposure L_{BC} by an equivalent exposure L_{BA} upon default of C. This modifies the network topology upon default of C but does not increase the number of links.

- In the case of *speculative* CDS i.e. when B has no exposure to C, default of C then has the effect of *triggering* a large exposure of B to A: a **new link** with large weight appears in the network. Typically C may be "distant" from A and B in the network.
- In the network terminology, they can be seen as contingent long-range links/shortcuts which appear in the graph when a default occurs.
- Adding a *small* proportion of CDS contracts in the networks can drastically change the topology of the network.
- Once the CDS are triggered the network behaves like a "small world".

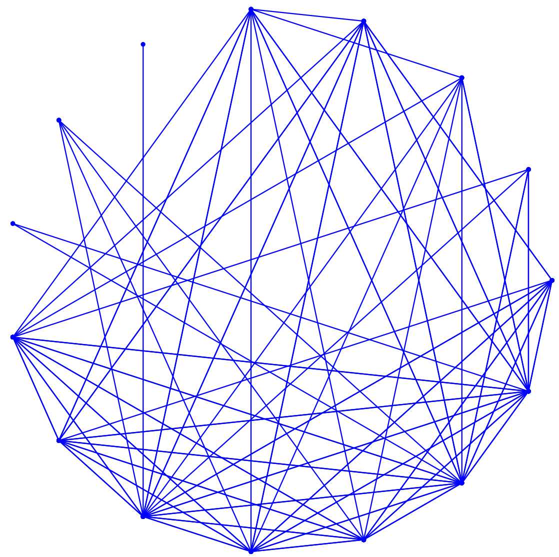

Figure 18: Dealer to dealer network: the 15 largest CDS dealers represent an almost complete network representing 61 % in terms of outstanding CDS notional

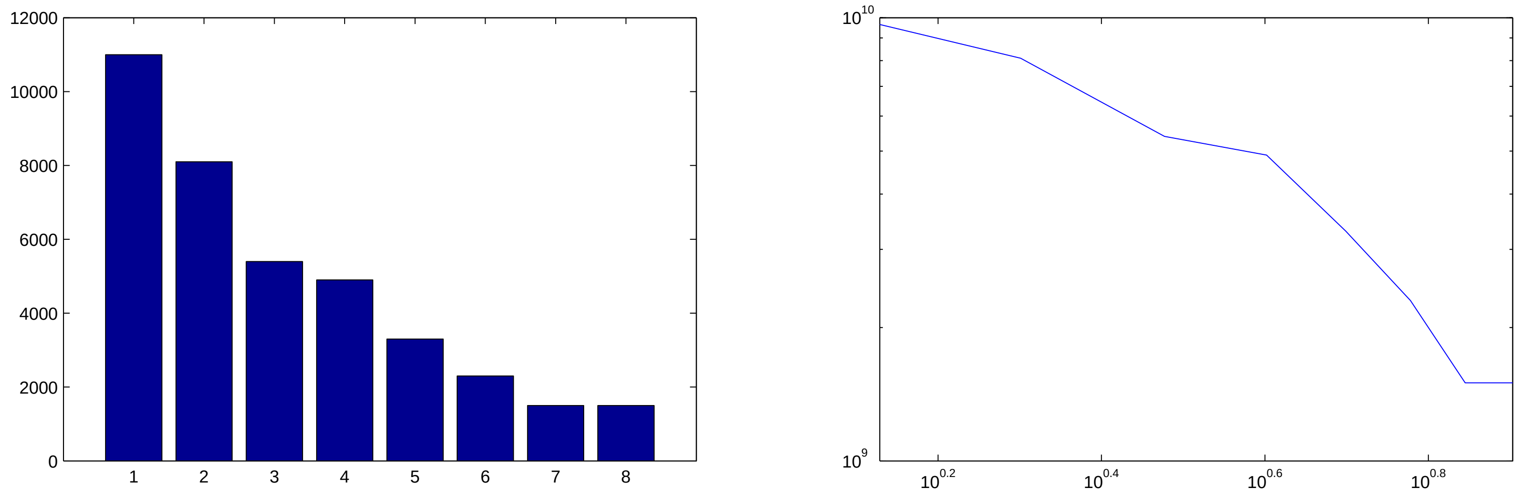

Figure 19: Rank diagram of largest CDS exposures of AIG in Sept 2008 exhibits an exponential tail.

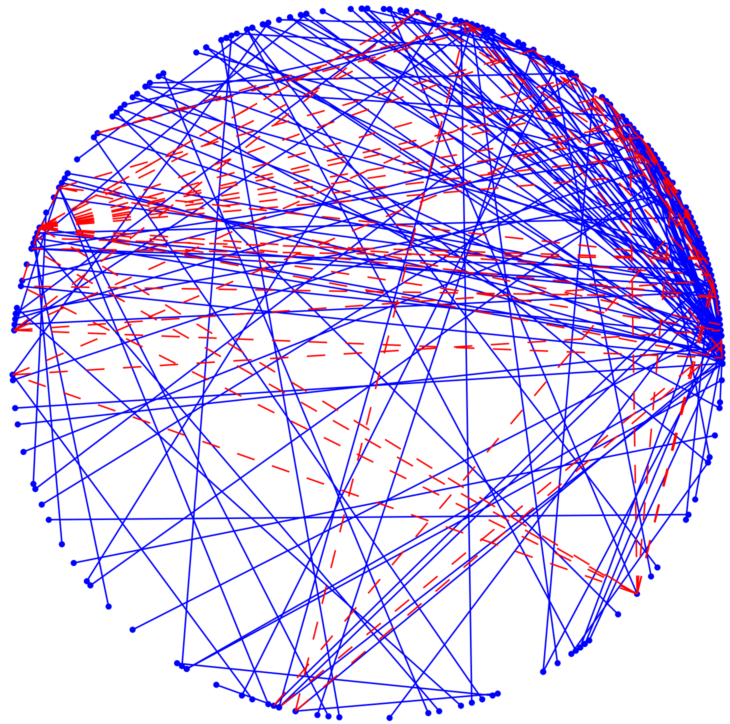

Figure 20: Default of a firm on which a lot of CDS protection has been sold can strongly affect exposures across the network. Blue: counterparty relations. Red: counterparty CDS exposures resulting from the default of a large name.

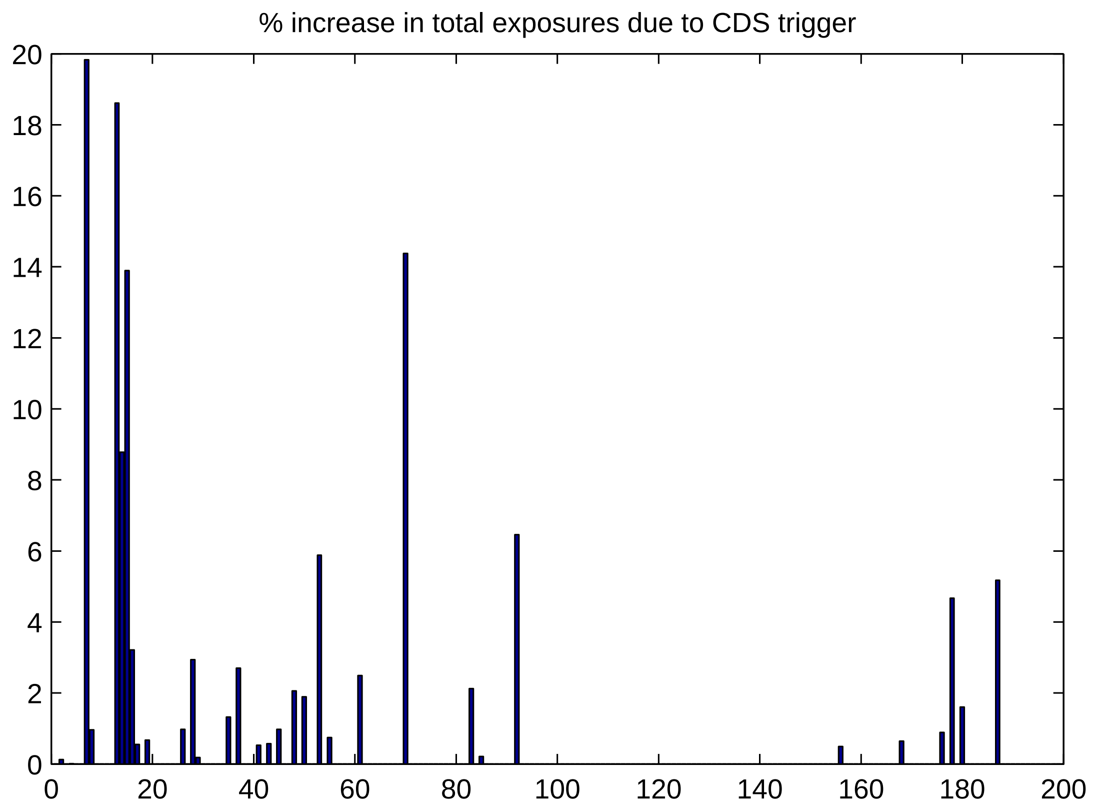

Figure 21: Increase in exposure sizes due to CDS triggered upon default of a large name.

Systemic impact of Credit Default swaps

- Simulation experiment: introduce a network of CDS contracts on top of an existing network of liabilities/exposures.
- total CDS notional = 20% of balance sheet sizes
- We vary the ratio of speculative/naked CDS to see the effect.
- Protection selling is limited to 'large' institutions (e.g. 100 largest in balance sheet size)
- CDS notionals have an exponential distribution
- Underlyings of CDS are 'large' institutions (index names)
- If i has sold protection to j on k for a notional N_{ij} then, upon default of k, i pays to j $N_{ij}(1-R)$, absorbing a loss:
  $c_i \to c_i - N_{ij}(1-R)$
  If $c_i < N_{ij}(1-R)$, the protection seller defaults.

Do credit default swaps increase or decrease systemic risk?

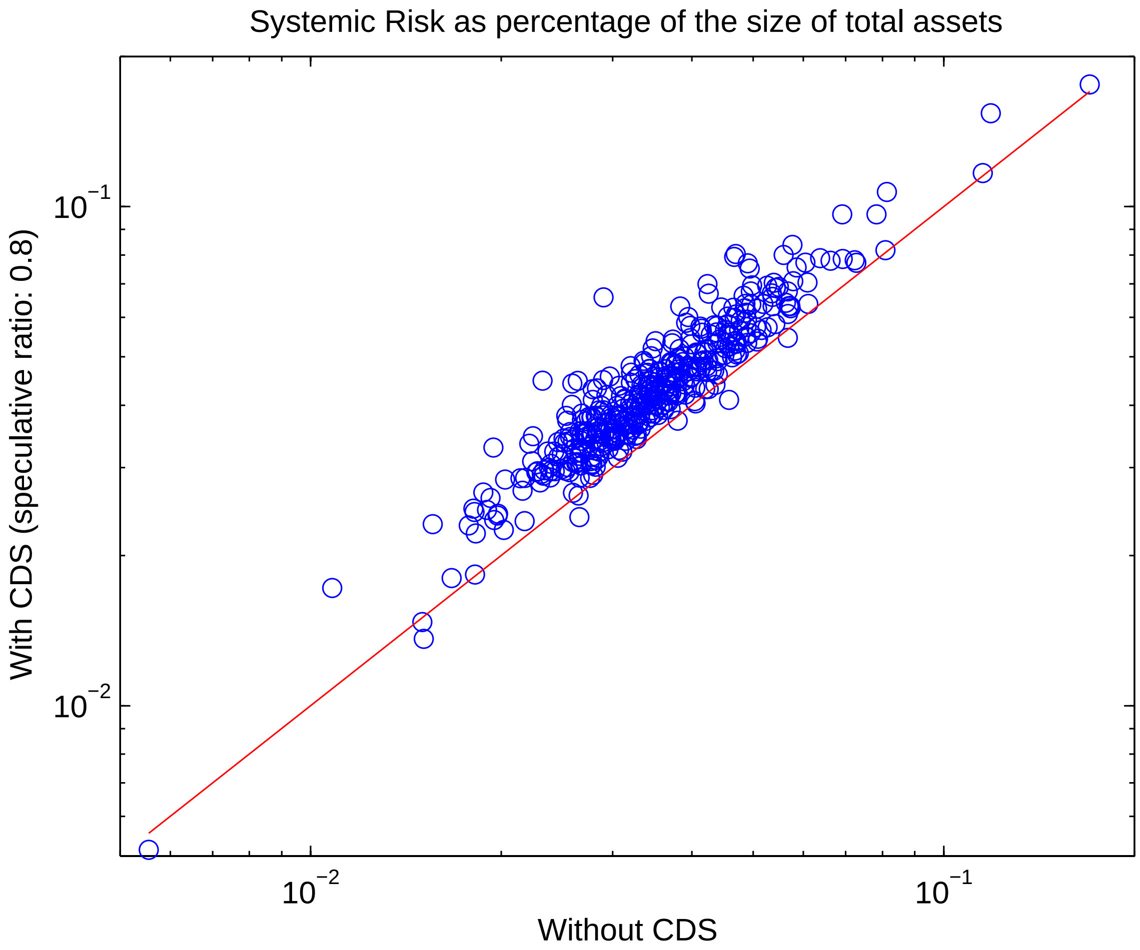

Figure 22: Effect of CDS on systemic risk index: total CDS notional = 20% of balance sheet sizes, 50% of CDS are speculative.

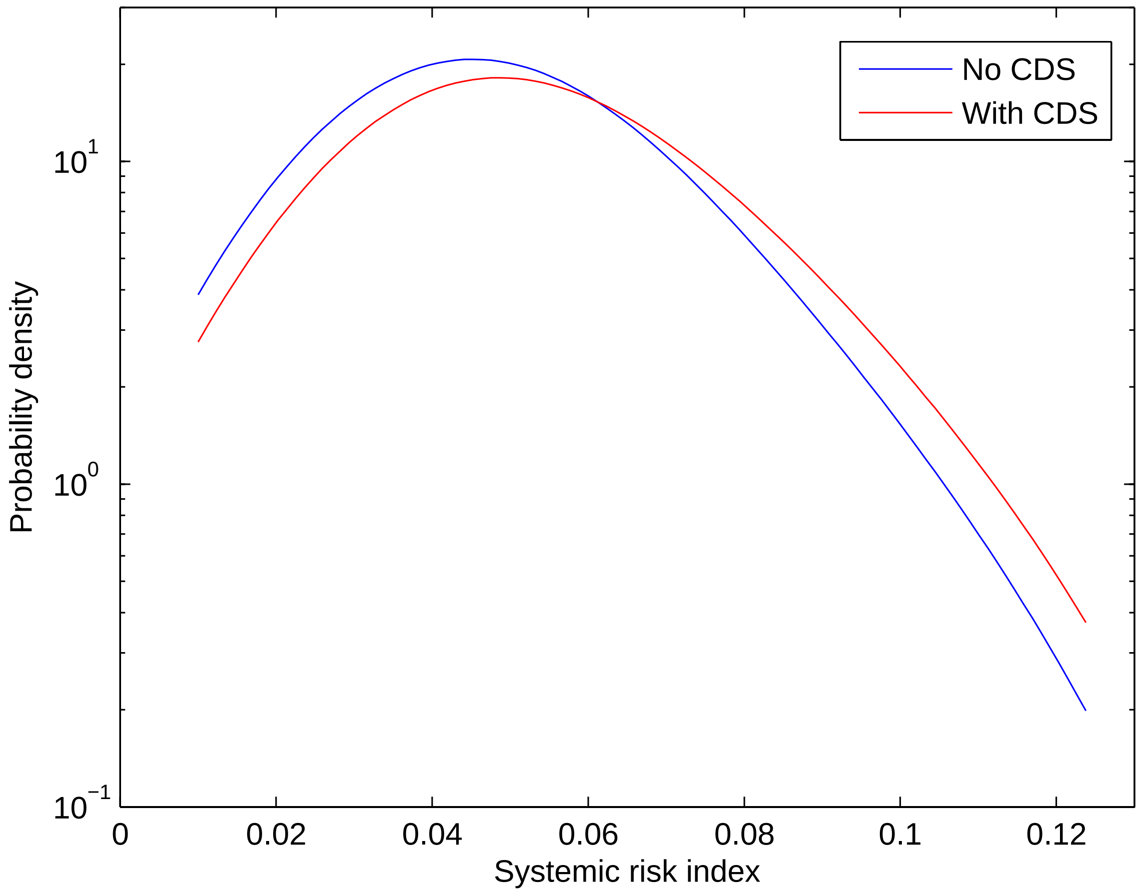

Figure 23: Effect of CDS on probability density of systemic risk index (kernel estimator): total CDS notional = 20% of balance sheet sizes, 50% of CDS are speculative.

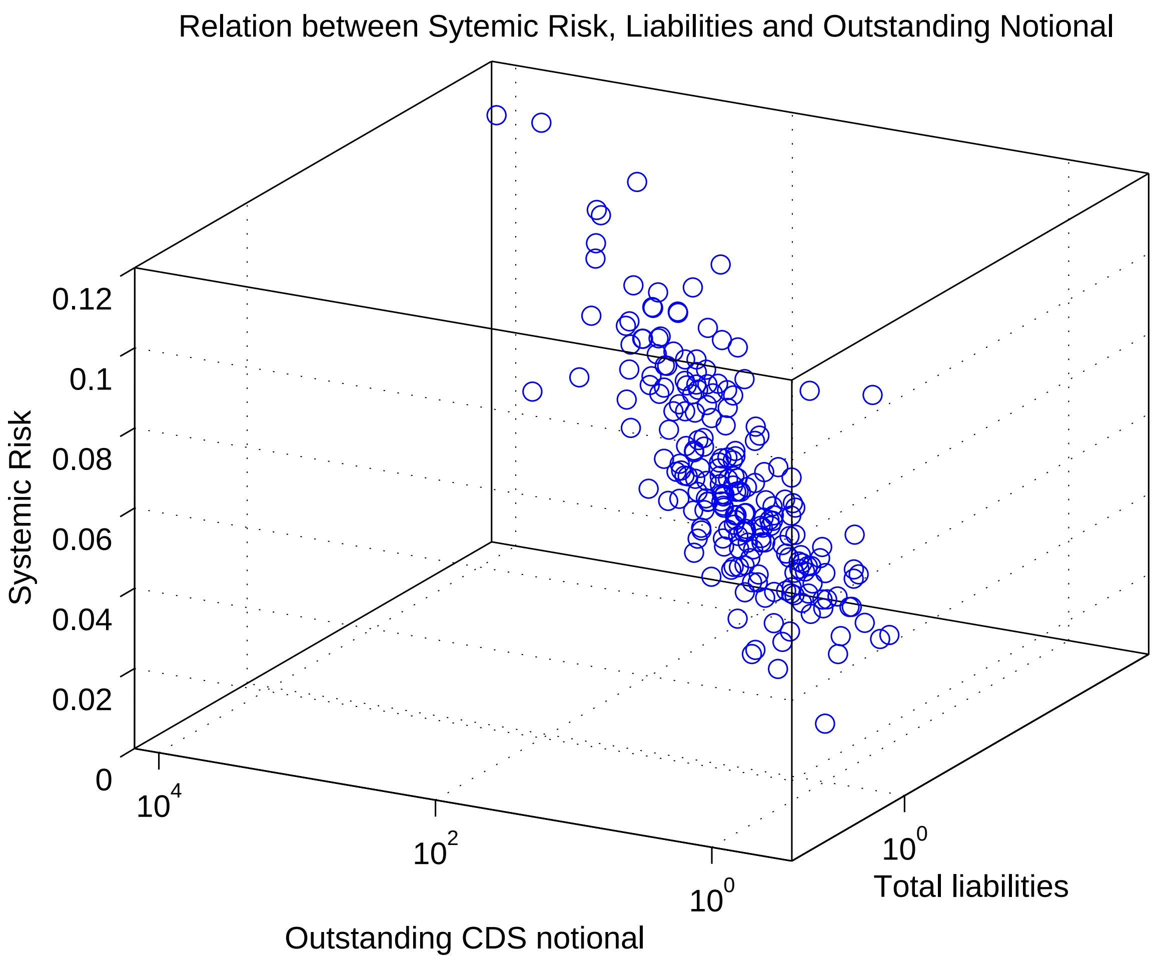

Figure 24: Names on which a large notional of CDS has been written can have a large systemic risk index as a result of the introduction of CDS markets.

Central counterparties and CDS clearinghouses

- Central counterparties (CCP) have been proposed as a possible solution to counterparty risk and systemic risk management in CDS and other OTC markets.
- Replace bilateral CDS trades between counterparties by two symmetric trades between CCP and each counterparty.
- Insulates counterparties from each others default: mitigation of counterparty risk, a major concern since 2008
- By centralizing information and supervision can facilitate supervision and transparency.
- Mitigates moral hazard: intervention for “bailing out” a CPP is less problematic than bailing out individual banks
- Does a central counterparty reduce systemic risk?

Effect of a CDS clearinghouse

The effect of a central counterparty can be modeled by adding a node to the CDS network and redirecting all CDS contracts into this node.

For the central counterparty, the role of the capital buffer is played by margin deposits + a "Guarantee fund". Each clearing participant contributes to a Guarantee fund.

The role of this fund is to reduce systemic risk by insulating clearing participants from the risk of the default of another clearing participant.

In accordance with BIS recommendations, the Guarantee Fund should cover losses associated with the simultaneous default of the largest clearing member in the event of deteriorating market conditions.

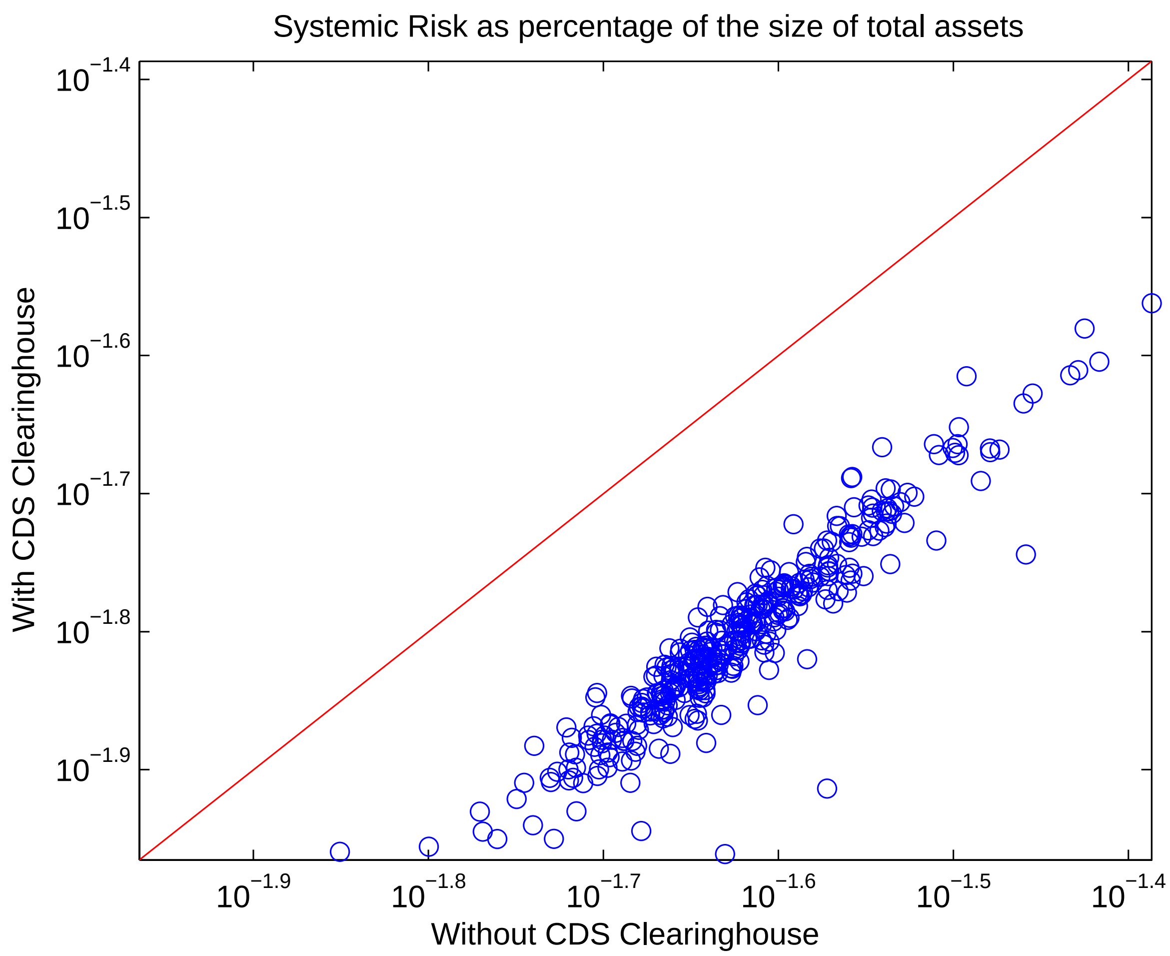

Figure 25: The Clearinghouse effect: Impact of a central counterparty on systemic risk index of financial institutions.

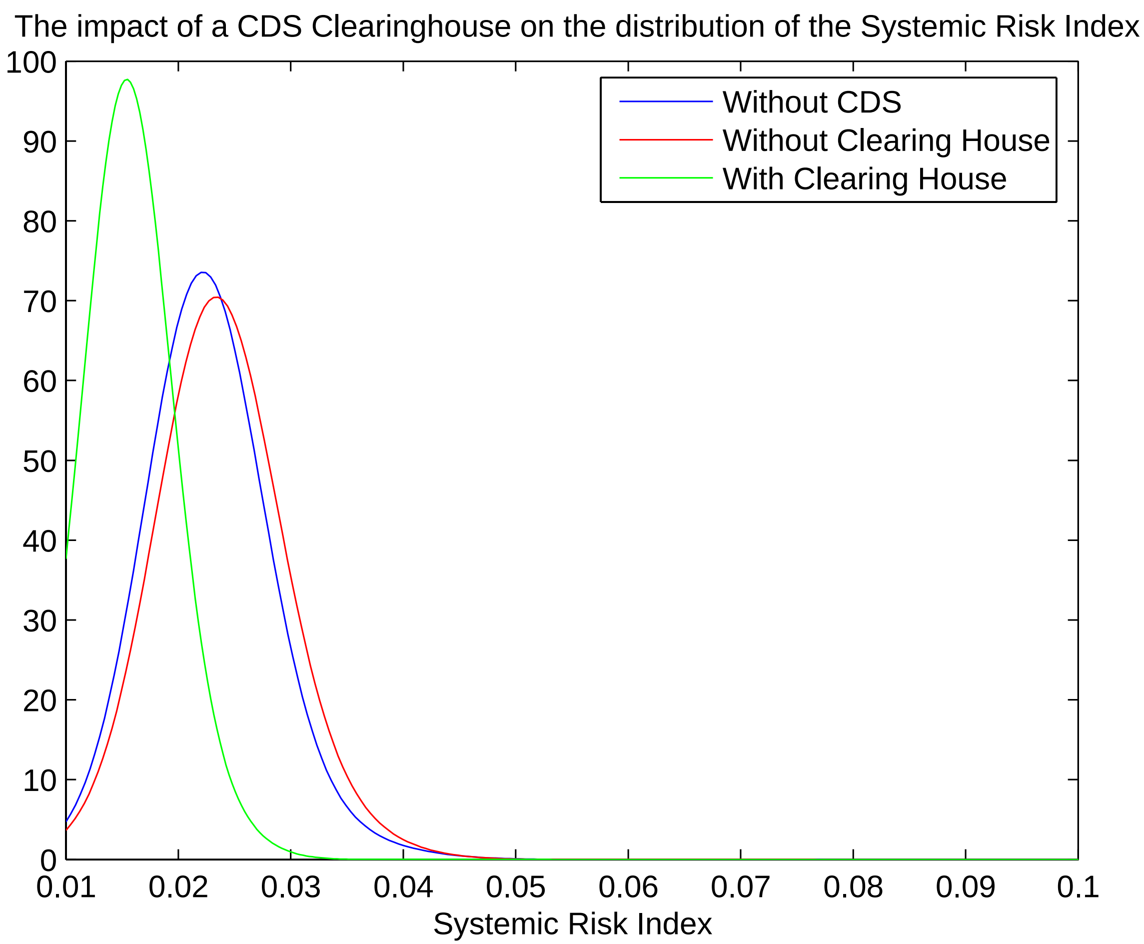

Figure 26: The Clearinghouse effect: Impact of a central counterparty on the distribution of systemic risk index of financial institutions.

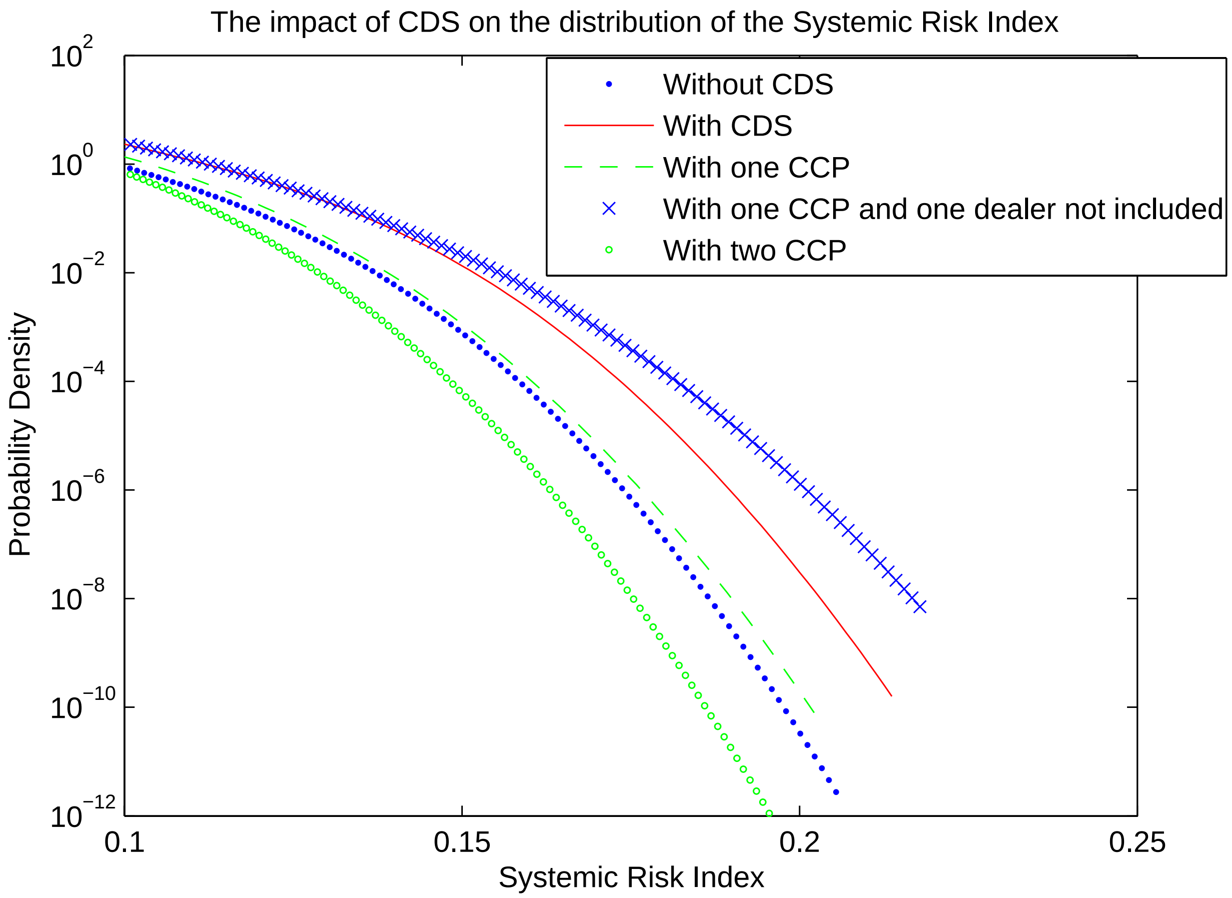

Figure 27: Impact of a central CDS clearinghouse on the distribution of the systemic risk index across institutions.

Implementation and regulatory implications

- In some countries (Austria, Brazil,..) this data is already available to regulators and our methodology can be implemented at the level of the national regulatory body.
- In all countries banks and various financial institutions are required already to report risk measures (VaR, etc.) on a periodical basis to the regulator.
- Our approach would require these risk figures to be a disaggregated across large counterparties: banks would report a VaR/risk figure for exposures to each large counterparty.
- Many large investment banks already compute such exposures on a regular basis so requiring them to be reported is not likely to cause a major technological obstacle.

Conclusions

- Measures of systemic risk need to account for **correlation in market shocks across firms** + **contagion effects** due to counterparty exposures. Focusing only on one of these two leads to an underestimation
- **Network models** provide useful insight into default contagion and systemic risk.
- We have a proposed a measure of the systemic impact of a (set of) institutions taking into account
  1. its connectivity with other market participants and the magnitude of its exposures: the Default Impact $DI(i)$
  2. the above + allowing for correlated market shocks across institutions during a crisis: the Systemic Risk Index $S(i)$.

- The systemic risk impact of the failure of an institution may have little correlation with size or conventional risk measures of its portfolio. It also depends on network properties: centrality, connectivity, and fragility -as measured by leverage of its neighbors/counterparties
- These criteria may be used as a tool in surveillance of systemic risk and for macro-prudential regulation.

- Actual capital, via the leverage coefficient, not risk-weighted capital seems to be a key determinant systemic risk.
- Imposing a cap on leverage is an effective mechanism for reducing default contagion and the probability of large systemic losses.
- Too big to fail/ Size is not the right criterion for determining systemic importance in absence of a maximal leverage ratio.
- Nodes with high systemic impact seem to be those who are major *counterparties* to large but fragile (high-leverage) nodes.
- Introduction of credit default swaps can increase default impact and systemic risk impact of large institutions
- Presence of a large notional volume of speculative credit default swap can distort the relation between systemic risk impact and firm properties (size, connectivity).

- The network approach allows to analyze in a meaningful way the systemic impact of credit default swaps. In particular it illustrates that credit default swaps introduce *contingent* long-range links between institutions that can increase the range of contagion.
- The network approach allows a meaningful cost/benefit analysis of the role of **clearinghouses** or central counterparties in mitigating systemic risk.
- Systemic risk involves understanding structure and dynamics of complex financial networks. Efficient methods for large scale simulation of realistic network models provide better insight than equilibrium models based on simplistic/homogeneous network structures.

References

- R Cont (2009) Measuring systemic risk, Working Paper.
- R Cont and A Moussa (2009) Too interconnected to fail: contagion and systemic risk in financial networks, Working Paper.
- E Bastos, R Cont, A Moussa (2009) The Brazilian baking system: network structure and systemic risk analysis, Working Paper.
- R Cont and A Minca (2009) Credit default swaps and systemic risk: a network approach, Working Paper.