Measuring Default Contagion and Systemic Risk: insights from network models

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Outline

1. Network models of financial markets

2. The structure of banking networks

3. Market-based vs exposure-based measures of systemic risk

4. Indicators for the systemic importance of a financial institution: the Contagion Index and Systemic Risk Index.

5. What makes an institution systemically important?

6. Credit default swaps and systemic risk

7. Macro-prudential regulation from the network perspective

Systemic risk in a financial system may be defined as the risk that a significant portion of the financial system fails to function properly. Simultaneous failure of several financial institutions may arise due to

1. **"correlation"**: exposure to common market factors may lead to simultaneous large losses across institutions. This "correlation" is exacerbated during a sell-off (feedback effects). Key issues: knowledge of holdings of financial institutions across asset classes and their exposures to various risk factors.

2. contagion via counterparty risk: the default of one institution may lead to writedowns of *assets* held by its counterparties, which may result in their insolvency.
   Key issues: network of counterparty exposures.

3. contagion via liquidity shocks: market moves and/or credit events may lead to margin calls/ derivatives payouts (e.g. trigger a CDS) which, if they exceeds the liquidity available to i, will lead to its default.
Key issues: understanding credit lines/ capacity to raise liquidity.

4. price-mediated contagion: even in absence of counterparty exposures, **feedback** effects may lead to contagion. Ex: fire sales/ massive deleveraging may depress prices and lead to **endogenous** volatility and correlation across assets.
Key modeling issues: understanding *price impact, market liquidity* and herd behavior/ feedback effects. (difficult)

The financial crisis has simultaneously underlined

- the importance of contagion effects and systemic risk

- the lack of adequate indicators for measuring and monitoring systemic risk.

- the lack of adequate data for computing such indicators

Many questions:

- designing **metrics** for systemic risk:
  Two different issues: global indicators (for the financial system) and measures of systemic importance (for a single institution or a group of institutions).

- analyzing the impact of micro/macro-prudential regulation on such measures of systemic risk

Network models as a framework for analyzing systemic risk

Based on theoretical arguments, empirical data and simulations, we argue that

- monitoring of exposures between financial institutions is necessary for monitoring systemic risk

- network models provide important insights for measuring the systemic impact of the failure of financial institutions

- heterogeneity of network structure is important: homogeneous models may give wrong insights

- Network models provide a meaningful analysis of the impact of credit derivatives on systemic risk

- Network models provide a natural framework for analyzing the impact of central clearing/ CCPs on systemic risk

The network approach to contagion modeling

A financial system is naturally modeled as a *network* of counterparty relations: a set of nodes and weighted links where

- nodes $i \in V$ represent financial market participants: banks, funds, corporate borrowers/lenders, hedge funds, monolines.

- (directed) links represent counterparty exposures: E_{ji} is the the (mark-to-market) exposure of i to j.

- In a market-based framework E_{ij} is understood as the fair market value of the exposure of i to j.

- Each institution i disposes of

  - a *capital* c_i for absorbing market losses. Proxy for c_i: Tier I capital.

  - a *liquidity* buffer l_i

| Assets A_i	Liabilities L_i
Interbank assets $\sum_j E_{ij}$ including: Liquid assets l_i^0	Interbank liabilities $\sum_j E_{ji}$ Deposits
Other assets a_i	Capital c_i

Table 1: Stylized balance sheet of a bank.

- Capital absorbs first losses.

- Default occurs if

  - (i) Demand for immediate payments (margin calls, derivative payouts) exceeds liquidity: $l_i + \sum_{j \neq i} \pi_{ij} < 0$
    Requires monitoring *liquidity reserves* and tracking *potential future exposures/payouts* from derivatives.

  - (ii) Loss due to counterparty exposure $> c_i \Rightarrow$ "insolvency"
    $\Rightarrow$ lenders cut off short term funding $\Rightarrow$ (i)

- *Actual*, not (Basel-type) "risk-weighted" value of exposures, assets and liabilities need to be considered.

Monitoring liquidity

Liquidity is harder to monitor: the true issue is the *capacity* of an institution to raise liquidity, not just current liquidity reserves. This depends on the credit lines given by lenders, which in turn depends on the current value of assets. We model the liquidity buffer as

$$l_i = \underbrace{l_i^0}_{\text{Liquid assets}} + \underbrace{A_i f(\frac{c_i}{A_i})}_{\text{Capacity for raising liquidity}}$$
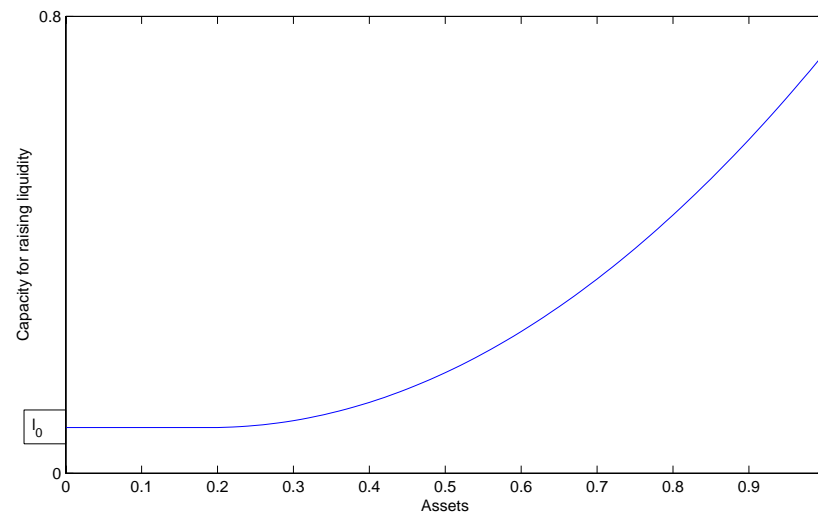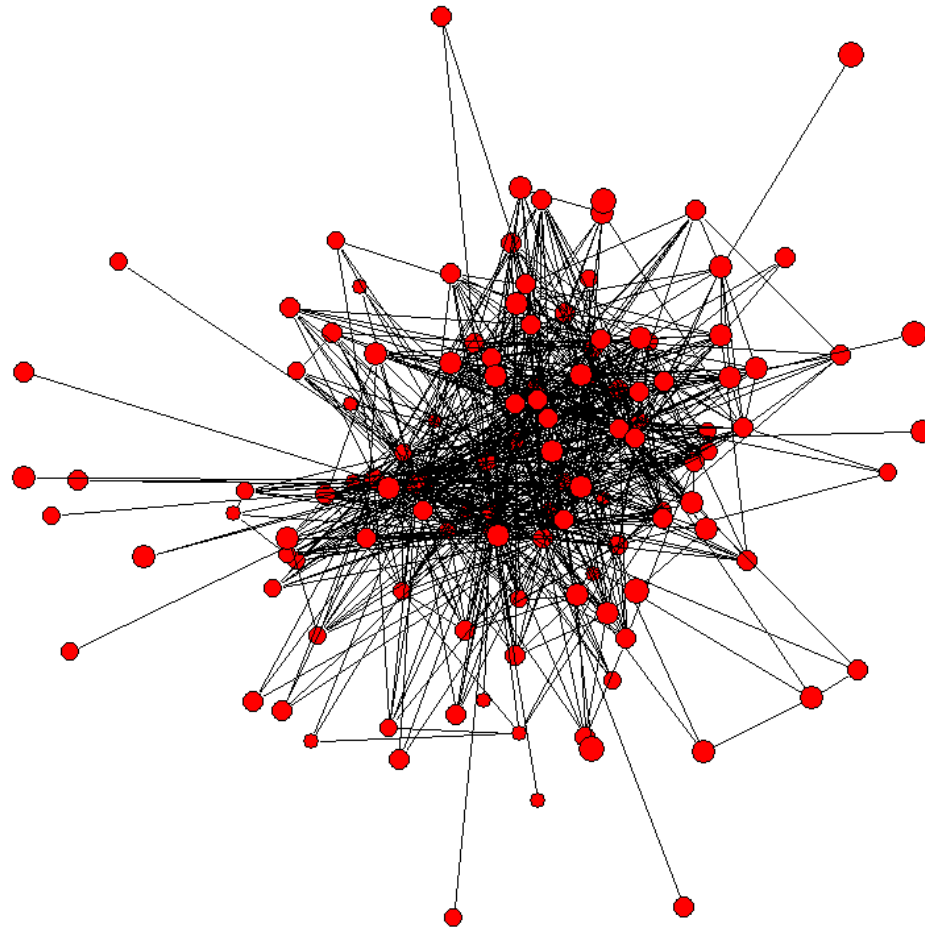
Network structure of banking systems

Figure 1: Brazilian financial network (Cont, Moussa & Santos 2009).

The Brazil financial system: a directed scale-free network

- Exposures are reportted daily to Brazilian central bank.

- Data set of all consolidated interbank exposures (incl. swaps)+ Tier I and Tier II capital (2007-08).

- $n \simeq 100$ holdings/conglomerates, $\simeq 1000$ counterparty relations

- Average number of counterparties (degree)= 7

- Heterogeneity of connectivity: in-degree (number of debtors) and out-degree (number of creditors) have heavy tailed distributions

$$\frac{1}{n}\#\{v, \mathrm{indeg}(v) = k\} \sim \frac{C}{k^{\alpha_{in}}} \qquad \frac{1}{n}\#\{v, \mathrm{outdeg}(v) = k\} \sim \frac{C}{k^{\alpha_{out}}}$$

  with exponents $\alpha_{in}, \alpha_{out}$ between 2 and 3.

- Heterogeneity of exposures: heavy tailed Pareto distribution with exponent between 2 and 3.

- Distributions are stable across time.
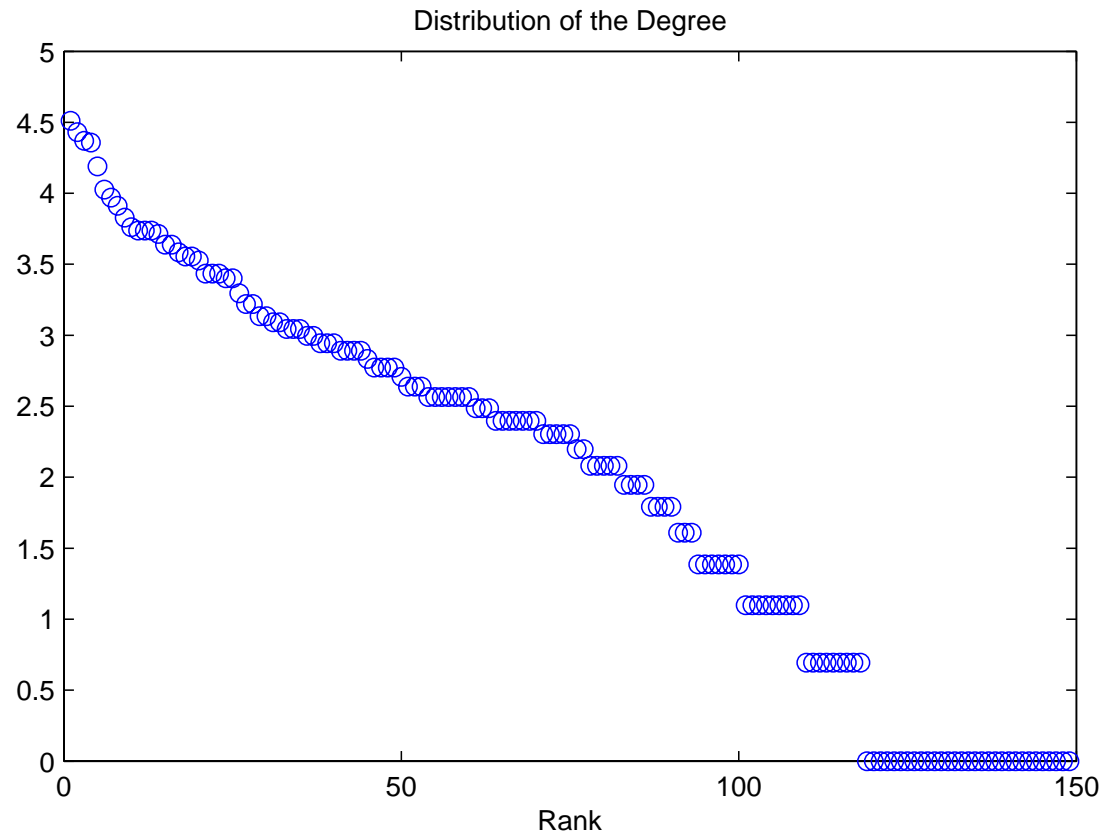
Distribution of the Degree

Figure 2: Brazilian financial network: distribution of degree (number of counterparties).
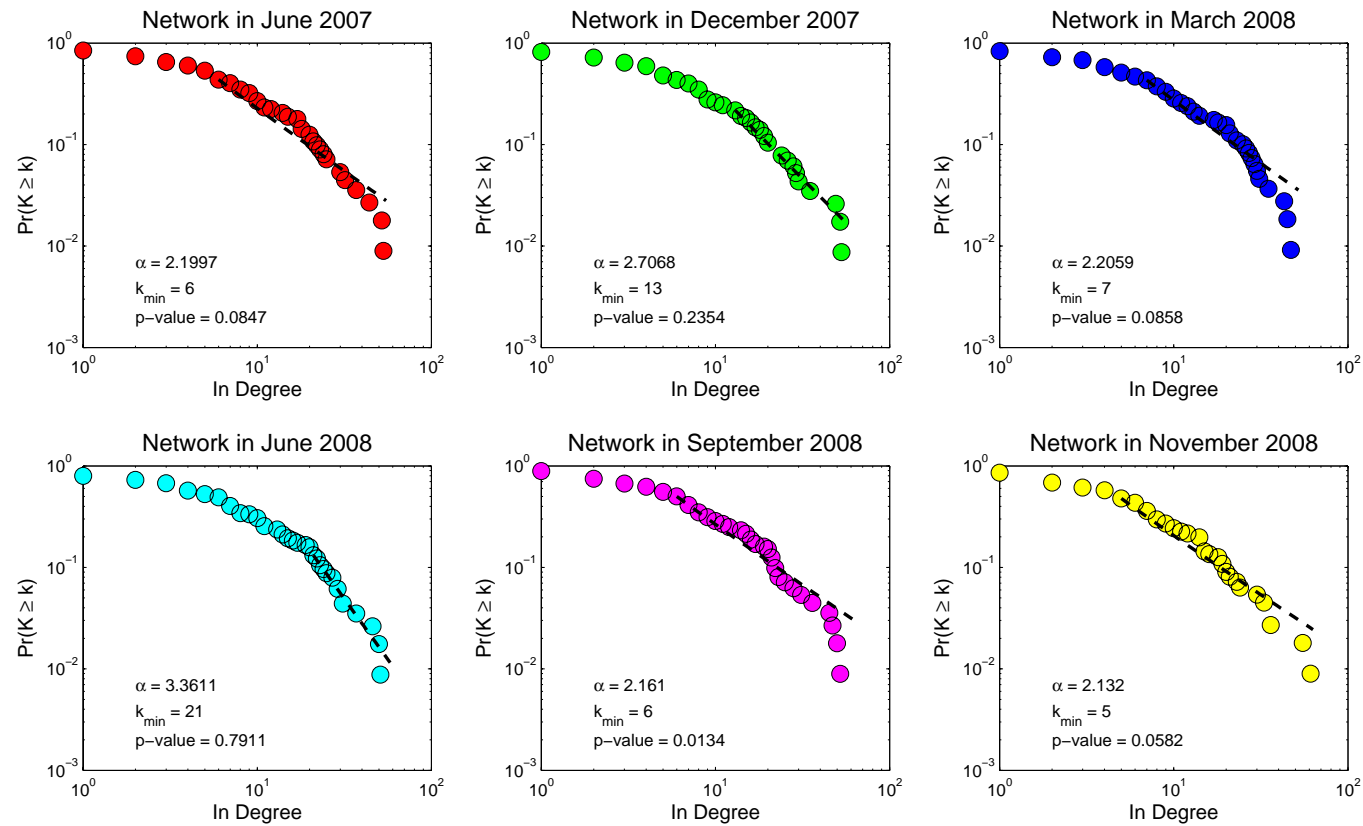
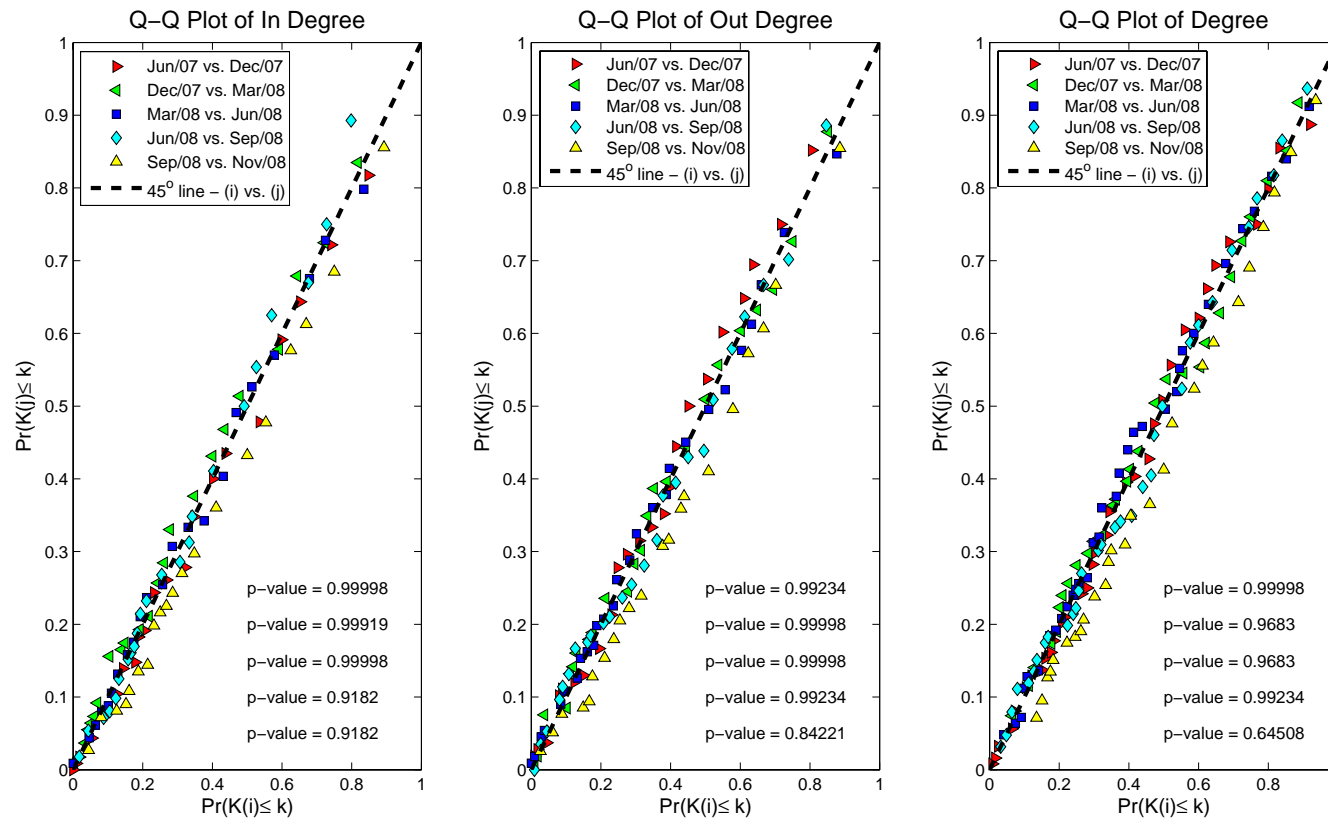Figure 3: Brazilian financial network: distribution of in-degree.

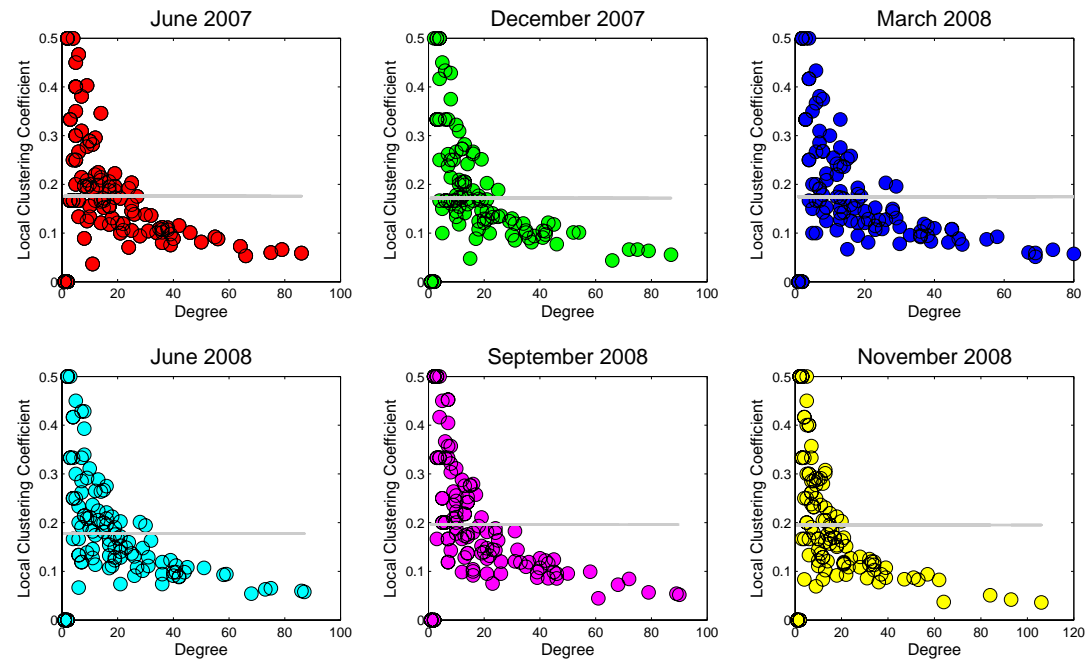Figure 4: Brazilian financial network: stability of degree distributions across dates.

Figure 5: Brazilian financial network: degree vs clustering coefficient. Arbitrarily small clustering coefficients rule out a small world network.
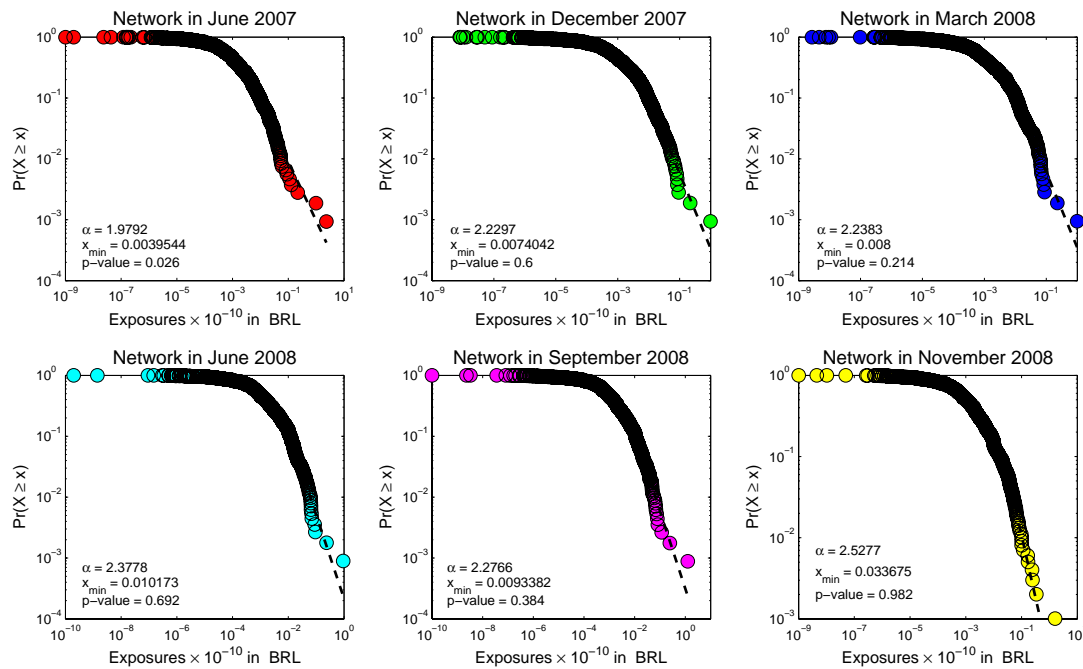
Figure 6: Brazilian network: distribution of exposures in BRL.

Measuring systemic risk: why exposures are important inputs

Market-based indicators have been recently proposed for quantifying

- contagion effects: CoVaR (quantile regression of past bank portfolio losses, Adrian & Brunnenmeier 2009)

- the (global) level of systemic risk in the financial system (Lehar 2005, Bodie, Gray, Merton 2008, IMF 2009, Huang, Zhu & Zhou 2010, Acharya et al 2010,..)

Useful for analyzing past/current economic data and should be part of any risk dashboard/ systemic risk tool kit.

Value as forward-looking diagnosis tools? any predictive ability?

Also: market-implied measures capture *market-perceived systemic risk*. Did market prices capture the systemic risk of AIG prior to its collapse?

Network approaches are based on **exposures** which represent potential **future** losses, which can give quite a different picture from past losses.

Even if we believe the Efficient Market hypothesis, market indicators need not reflect exposures, which are not public information.

Regulators, on the other hand, have access to non-public information on exposures and should use such information for stress testing and for computing systemic risk indicators.

OBJECTIVES

- Develop *forward-looking* indicators for measuring the systemic impact of the failure of a large financial institution, which can serve as a early warning of potential future systemic losses

- 3 measures: Default impact, the Contagion Index and the Systemic Risk Index

- These indicators combine the effects of

  - **correlation**: common market factors affecting defaults/losses

  - **network contagion effects**: default contagion via counterparty risk and via liquidity shocks

  - indirect contagion via **credit risk transfer** (CDS,CDO)

- and provide tools for studying the influence of macroprudential policies on systemic risk

Contagion in financial 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).

Domino effects in financial 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) or FedFunds exposures and report very small loss magnitudes (in % of total assets).

Contagion effects: too rapidly dismissed?

The small magnitude of such "domino" effects has been cited as justification for ignoring contagion (Furfine 2003, Geneva Report 2008).

Such simulations ignore the impact of correlated market shocks on bank balance sheets and, therefore, the compounding effect of market shocks and contagion.

Many studies on domino effects are not based on actual exposures but either look at a subset of exposures (e.g. FedWire) or *estimate/reconstruct* exposures from balance sheet data using maximum entropy methods (Boss et el, Elsinger et al) which result in distributing exposures as uniformly as possible across 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 balance sheets.

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

Measuring the systemic impact of a default

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

Defaults can occur through

1. (correlated) market shocks to balance sheets
   $c_i \mapsto \max(c_i + \epsilon_i, 0)$

2. counterparty risk: default of i may lead to default of j if
   $c_j < (1 - R_i)E_{ji}$

3. lack of liquidity: if margin calls/ derivative payouts π_{ij} exceed available liquidity $l_i + \sum_j \pi_{ij}(c + \epsilon, E) < 0$

In cases 2 and 3 this can generate a 'domino effect' and initiate a cascade of defaults.

Default cascades and default impact

Given an initial set A of defaults in the network, we define a sequence $D_k(A)$ of default events by setting $D_0(A) = A$ and, at each iteration, identifying the set $D_k(A)$ of institutions which either

- become *insolvent* due to their counterparty exposures to institutions in $D_{k-1}(A)$ which have already defaulted at the previous round

$$c_j^k = \min(c_j^{k-1} - \sum_{v \in D_{k-1}(A)} (1 - R_v)E_{jv}, 0) \qquad (1)$$

- lack the *liquidity* to pay out the contingent cash flows $\pi_{jv}(c^{k-1}, E^{k-1})$–margin calls or derivatives payables– triggered by the previous credit/market events:

$$l_j + \underbrace{\sum_{v \notin D_{k-1}(A)} \pi_{jv}(c^{k-1}, E^{k-1})}_{} < 0 \qquad (2)$$

Definition 1 (Default cascade). *Given the initial default of a set A of institutions in the network, the default cascade generated by A is defined as the sequence*

$$D_0(A) \subset D_1(A) \subset \cdots \subset D_{n-1}(A)$$

where $D_0(A) = A$ and for $k \geq 1$,

$$c_j^k = \min(c_j^{k-1} - \sum_{v \in D_{k-1}(A)} (1 - R_v)E_{jv}, 0) \quad (3)$$

$$D_k(A) = \{j, \quad c_j^k = 0 \quad \text{or} \quad l_j + \underbrace{\sum_{v \notin D_{k-1}(A)} \pi_{jv}(c^k, E) < 0}_{\text{cash flows triggered by current defaults}} \quad \}$$

The cascade ends after at most $n - 1$ rounds: $D_{n-1}(A)$ is the set of defaults generated by the initial default of A.

DEFAULT IMPACT of a financial institution

Case of a single default:, $D_{n-1}(i) =$ cascade generated by default of i.

We define the "default impact" $DI(i, c, l, E)$ of i as the total loss (in \$) along the default cascade initiated by i.

$$DI(i, c, l, E) = \underbrace{\sum_{j \in D_{n-1}(i)} (c_j + \sum_{v \notin D_{n-1}(i)} (1 - R_j)E_{jv})}_{\text{sum over defaults generated by i}}$$

$DI(i, c, l, E)$ depends -in a deterministic way- on the network structure: matrix of exposures $[E_{jk}]$, liquidity reserves l_j, capital c_j.

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

Default contagion under market stress: the Contagion index

We now combine the

(deterministic) computation of Default Impact and the

(stochastic) simulation of correlated defaults over a short horizon

to define the Contagion Index of the institution i as

$$CI(i) = E[DI(i, c + \epsilon, l, E)|c_i + \epsilon_i \leq 0]$$

where $\epsilon = (\epsilon_i, i \in I)$ are correlated market shocks generated according to a factor model.
$CI(i)$ is the expected loss in the cascade generated by the failure of i, in the scenarios where i defaults due to market shocks.

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

To simulate shocks one may use factor models commonly used in portfolio default risk simulations.

Ex 1: Gaussian one-factor model ϵ_i

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

where Z_i are IID N(0,1).

Ex 2: a heavy-tailed factor model

$$c_i = F_i^{-1}(G_\alpha(X_i)) \qquad X_i = (\rho^{1/\alpha}Z_0 + (1-\rho)^{1/\alpha}Z_i)$$

where $Z_i \sim G_\alpha$ are IID α-stable with $\alpha \in]0,2[$.

Ex 3: a dynamic factor model

$$dc_i(t) = \mu c_i(t)dt + \sigma_i c_i dW_t^i$$

where $\mathrm{cov}(W_t^i, W_t^j) = \rho_{ij}t$.

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

Systemic Risk Index of a financial institution

The mere occurrence of defaults/losses in the financial system is not a manifestation of systemic risk. For ex, if a large hedge funds whose counterparties are essentially hedge funds defaults, this may not affect the banking system

Usually systemic risk refers to the situation where losses/defaults occur among lending institutions (e.g. commercial banks), which then has the potential of disrupting the real economy.

To capture this feature, we define a set $\mathbb{C}$ of core institutions, constituted of lending institutions whose default is considered harmful/undesirable.

Systemic Risk Index of a financial institution

We define the **Systemic risk index** of an institution i on $\mathbb{C}$ as the loss incurred to core institutions by the default of i:

$$L_{\mathbb{C}}(i, c, E) = \underbrace{\sum_{i \in D_{n-1}(i) \cap \mathbb{C}} \left(c_i + \sum_{j \in \mathbb{C} - D_{n-1}(i)} (1 - R_i) E_{ji} \right)}_{\text{sum over } \textbf{core} \text{ defaults generated by A}}$$

We then define the Systemic Risk Index of i as the expected default impact of i on core institutions, given that i defaults due to market shocks:

$$S(i) = E[L_{\mathbb{C}}(i, c + \epsilon, E) | c_i + \epsilon_i \leq 0]$$

High value of $S(i)$ indicates that the default of i can generate a large loss among core lending institutions even if i is not one of them.

Contagion and systemic impact of a group of institutions

Similarly we can define the contagion index 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:

$$S(A) = E[DI(A, c + \epsilon, E) | \forall i \in A, c_i + \epsilon_i \leq 0]$$

S then defines a set function

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

which associates to each group A of institutions a number quantifying the loss inflicted to the financial system if institutions in the set A fail.

The Systemic Risk Index can be viewed, from the point of view of the *regulator*, as a macro-level "risk measure".
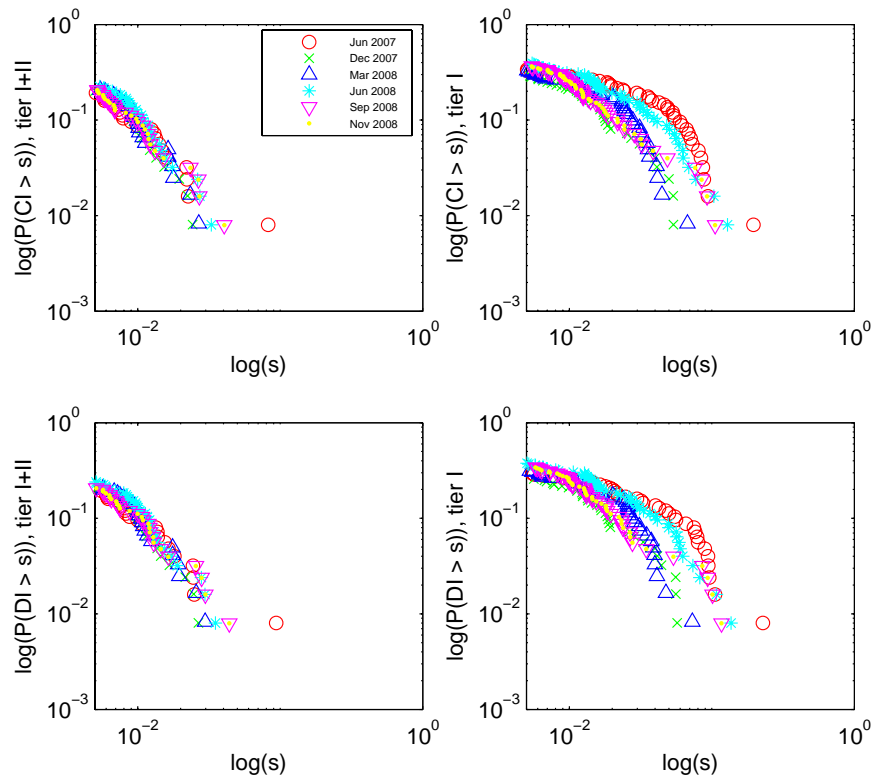
Figure 7: Brazilian network: distribution of *default impact* and *contagion index* across institutions (c_i = Tier I capital). Tails amplify in June 2007 and June 2008.
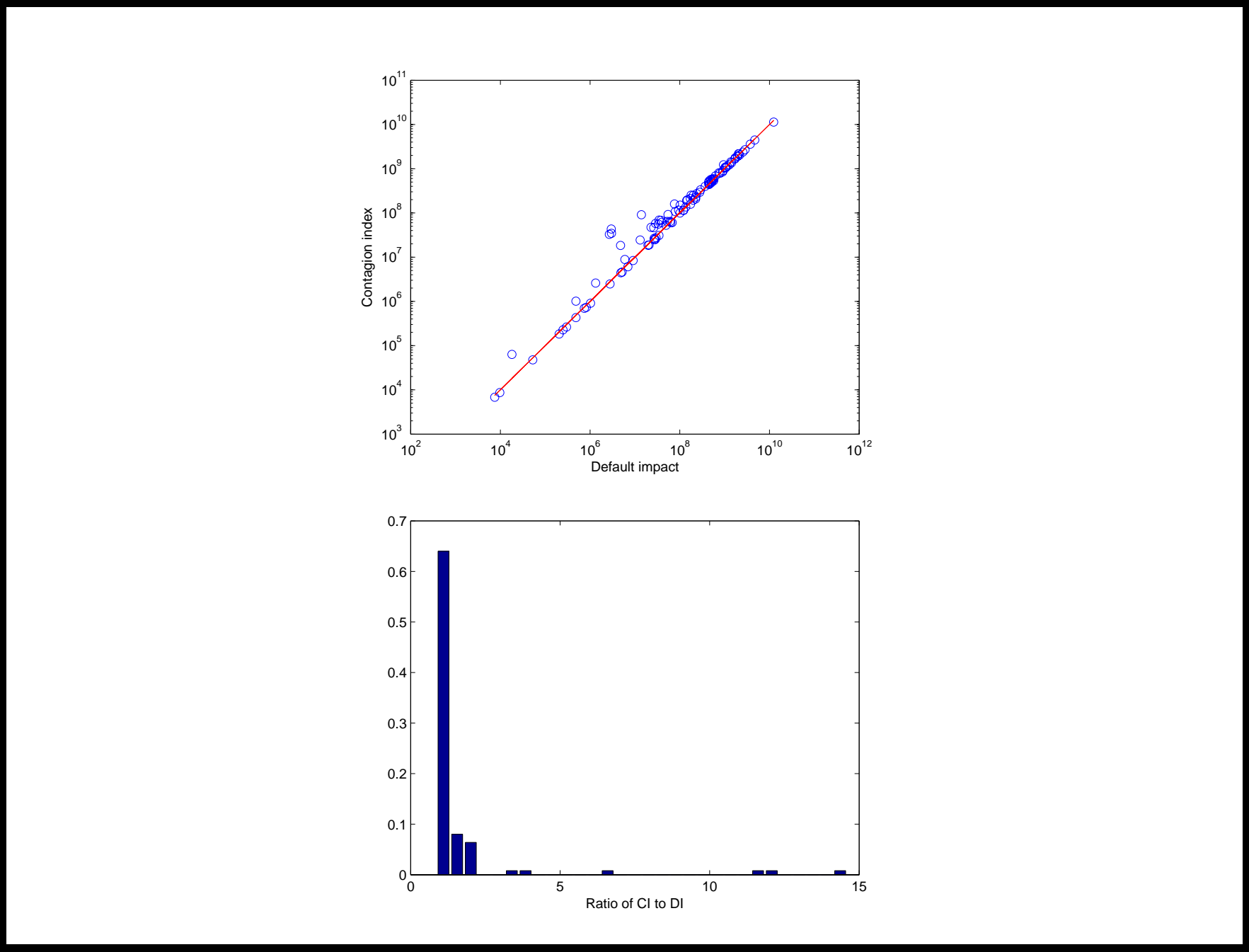
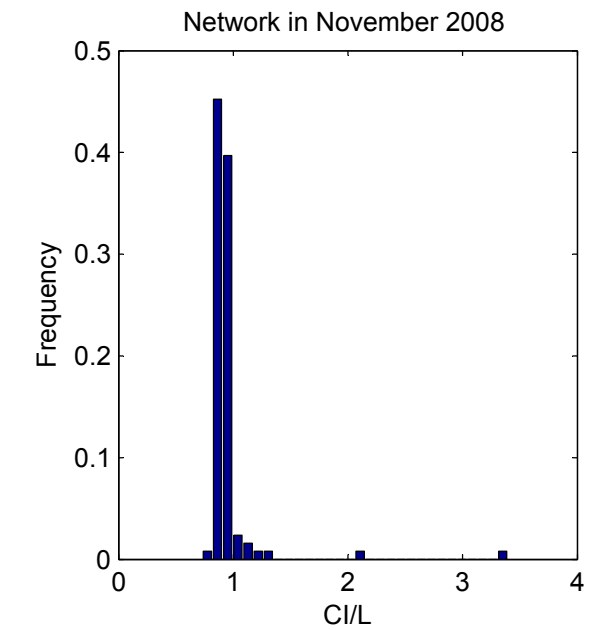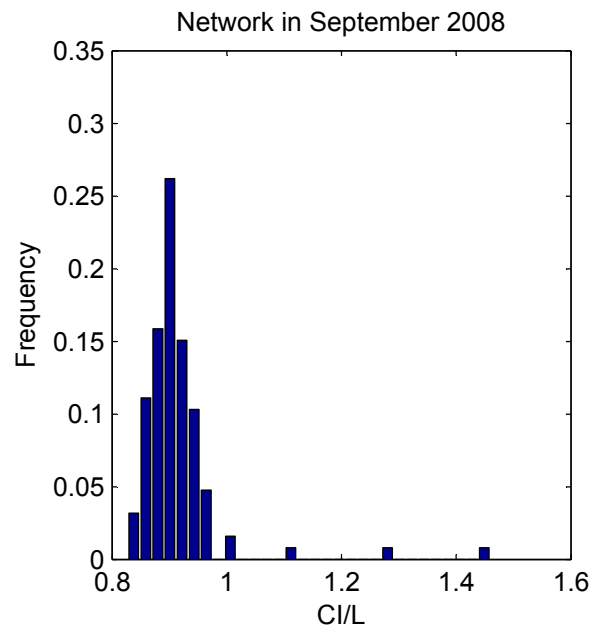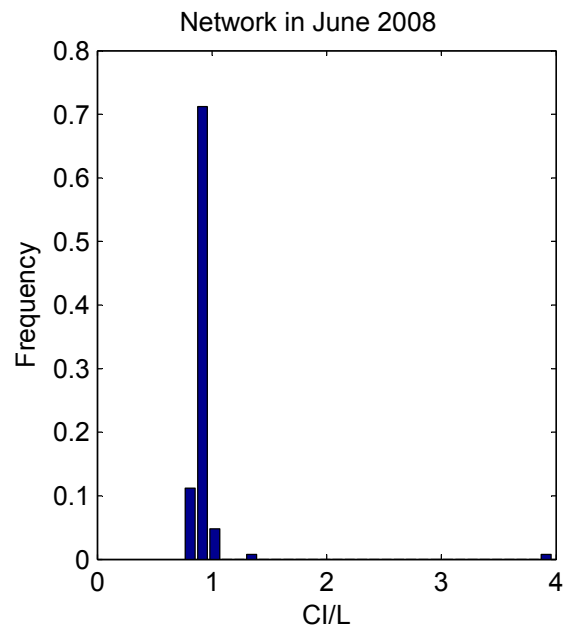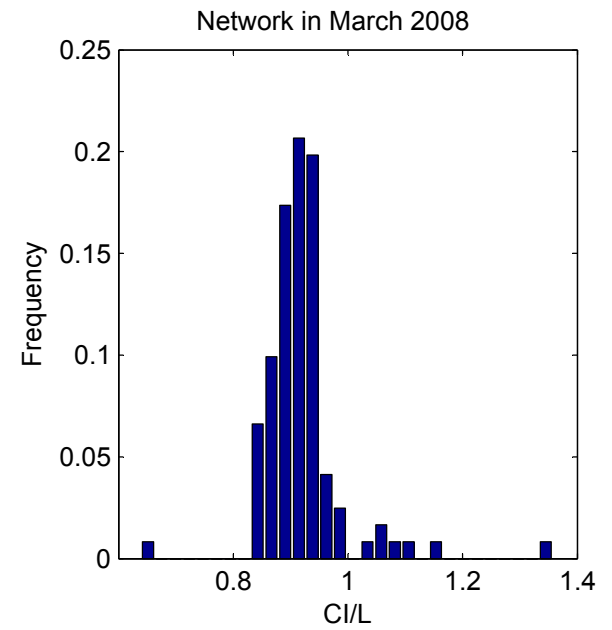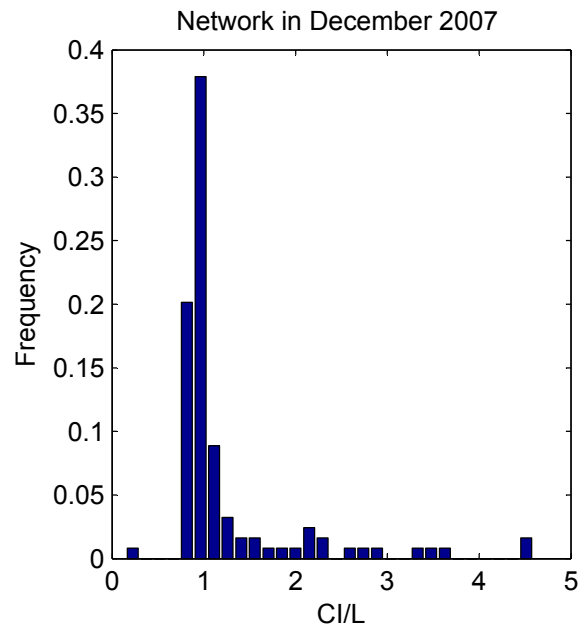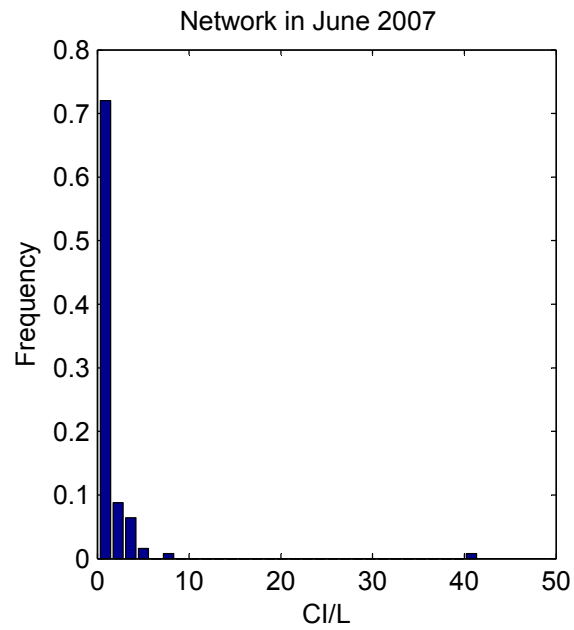Figure 8: *Default impact* vs *contagion index*: *contagion index* can
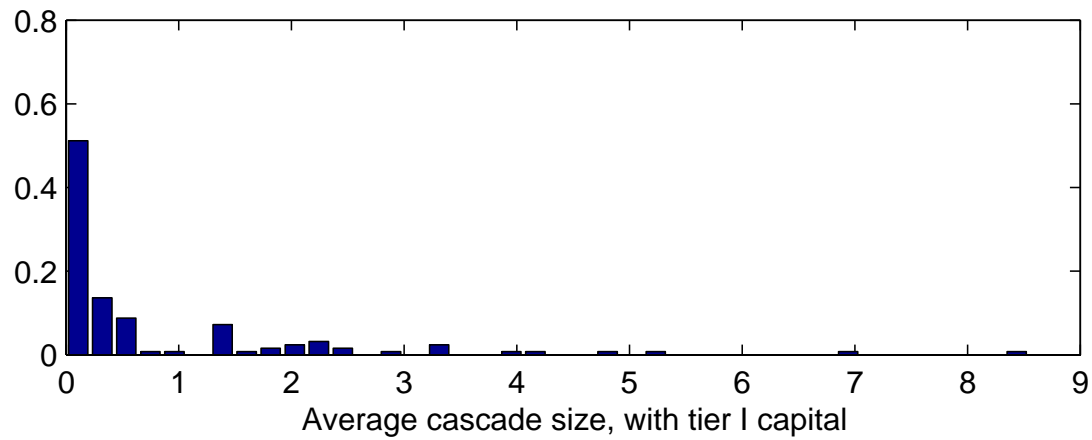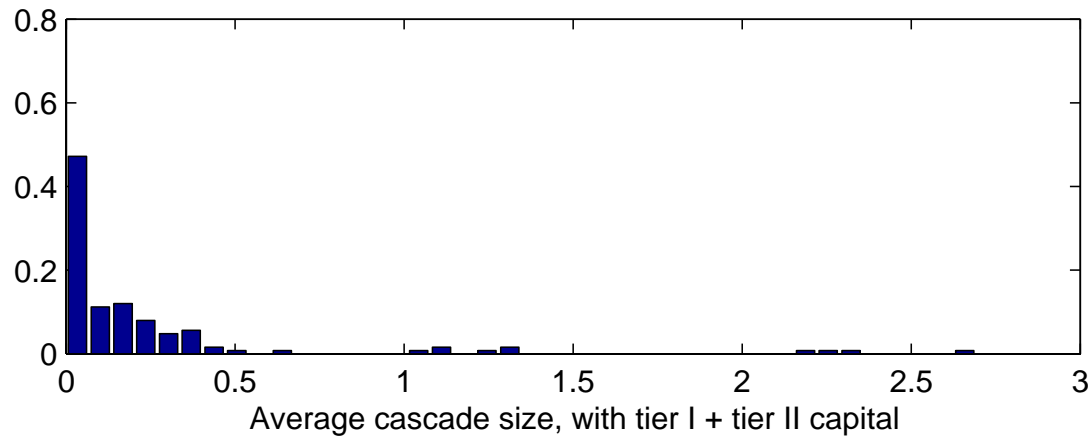
Figure 9: Distribution of the average size of default cascade generated by a given institution.

i	S(i)	Loss due to Contagion	Loss due to fund. default
81	0.17	0.15	0.02
134	0.15	0.12	0.03
10	0.15	0.12	0.03
287	0.13	0.11	0.02
40	0.12	0.07	0.05
Network average	0.06	0.04	0.03
Network median	0.05	0.03	0.03

Table 2: Contribution of default contagion to the systemic risk index
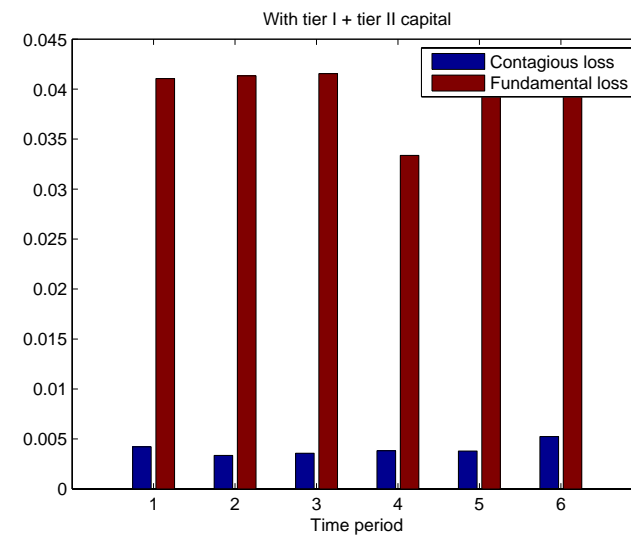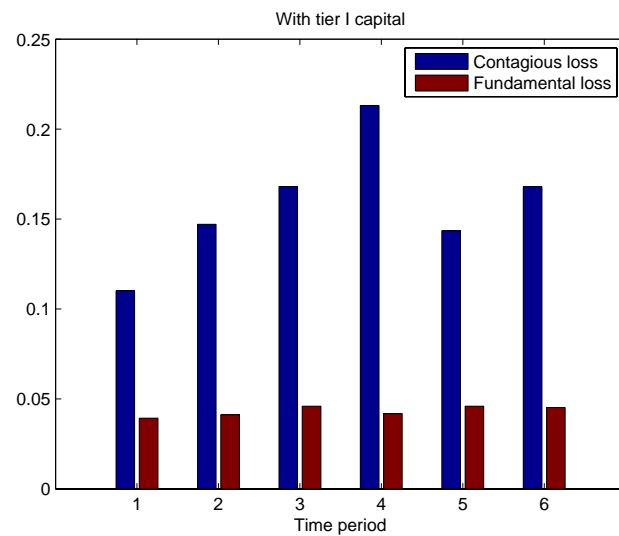
Figure 10: The fundamental loss is the main source of systemic risk when considering Tier I + Tier II as Reference capital. However, when using Tier I capital, the contagion loss prevails.

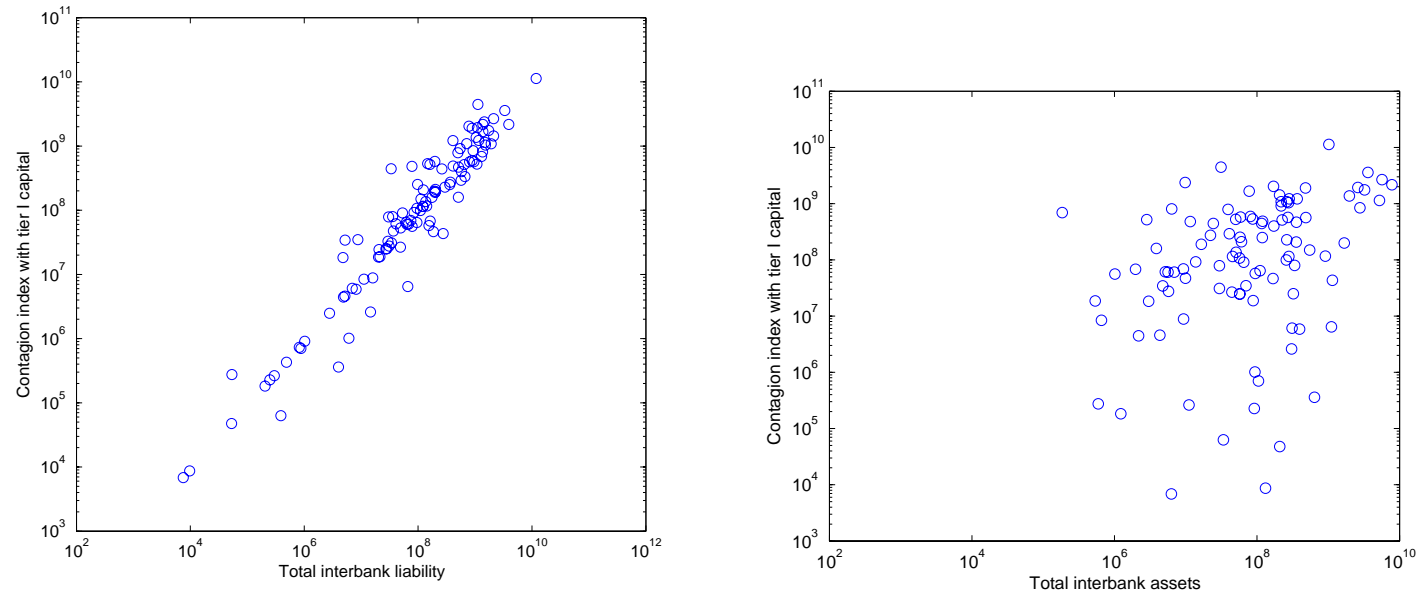# What makes an institution systemically important?

Figure 11: Size does matter: systemic risk index vs total interbank liability (left) and total interbank assets (right).

Node	Contagion index	Number of counterparties	Total liability
29	11.31	30	11.84
13	4.45	21	1.12
48	3.58	21	3.32
5	2.67	41	2.13
60	2.38	7	1.45
Network average	0.51	8.98	0.47
Network median	0.08	6.00	0.08

Table 3: Analysis of the five most contagious nodes, when using tier I capital for the time period June 2008. Unit: Billion $.

Measures of Leverage, Frailty and Susceptibility

Total liabilities $L_i = \sum_j E_{ji}$

Leverage of i: ratio of total liability to capital buffer

$$l(i) = \frac{\sum_j E_{ji}}{C_i} = \frac{\text{Total interbank exposure}}{\text{Capital buffer}}$$

Susceptibility: maximal fraction of capital wiped out by one default

$$\chi_i = \max_{j \neq i} \frac{E_{ij}}{C_i} = \max_j \frac{\text{Exposure of i to j}}{\text{Capital buffer of i}}$$

Local network frailty (at node i):

$$f_i = \chi_i L_i = \max_{j \neq i} \frac{E_{ij}}{C_i} \sum_{j \neq i} E_{ji} = l(i) \max_{j \neq i} E_{ij}$$

Counterparty frailty: maximal frailty of counterparties of i

$$CF_i = \max_{j, E_{ji} > 0} f_j \qquad CS_i = \max_{j, E_{ji} > 0} \chi_j$$

i	S(i)	OutDegree (claimants)	L_i	Local frailty f_i	CF_i
81	0.17	9	276.37	35.82	182
134	0.15	8	130.62	22.71	145
10	0.15	77.97	182.62	246	
287	0.13	2	158.77	0.73	45
40	0.12	16	45.25	40.85	182
Network average	0.06	5.76	13.76	26.12	26
Network median	0.05	4.00	6.39	6.10	6.1

Table 4: Analysis of the five nodes with highest systemic risk index.

Stepwise regression based on maximum adjusted R^2 identifies the following covariates as having the highest correlation with the Systemic Risk index of a node

- total liability size $L_i = \sum_j E_{ji}$

- counterparty frailty: CF_i

L_i	$\ln(CF_i)$	$\ln(f_i)$
74.76	40.84	37.57

Table 5: Correlation with the systemic risk index (in %)

The systemic impact of an institution cannot be determined from its aggregate portfolio risk (VaR, Expected Shortfall etc.).

An institution i whose counterparties are large, leveraged and have high susceptibility to the default of i, will typically exhibit a large Systemic Risk Index. This is measured by the "counterparty frailty".

Contagion in channeled through "dangerous links" -exposures which represent high fraction of capital.

Monitoring *exposure ratios*- ratio of capital to largest exposure, as opposed to total assets- signals such "dangerous links".

Influence of regulatory policies on systemic risk

1. Minimal capital ratio: ratio of capital buffer to total interbank exposures

2. Maximal susceptibility ratio = minimal ratio of capital buffer to any **single** exposure.

In both cases: based on actual, not risk-weighted, exposures/assets.

Imposing a cap γ on the susceptibility ratio means ensuring that no single default can wipe out more than $\gamma\%$ of the capital of the institution.

Targeted capital requirements: require higher capital for critical nodes in the networks. Analogy with targeted immunization in epidemiology.
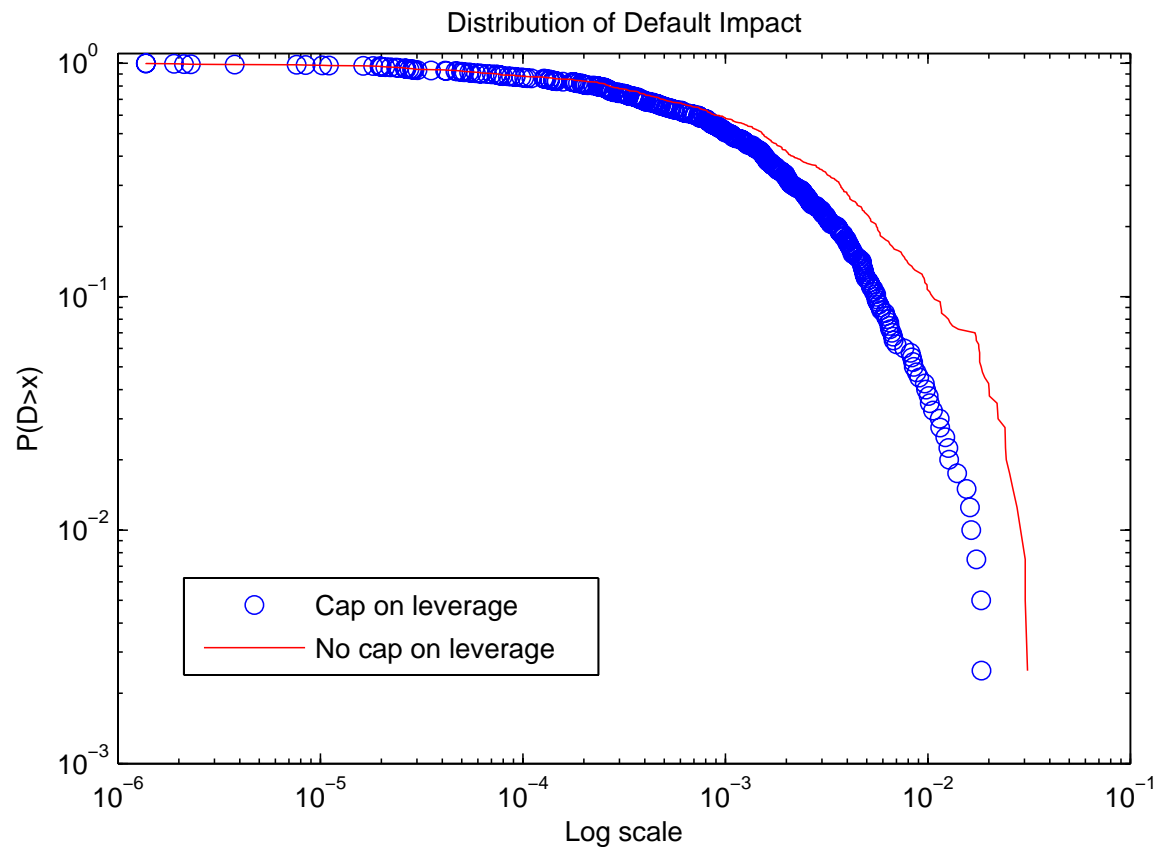
Figure 12: Influence of capital ratio on default impact: requiring a minimal (non-weighted) capital ratio reduces the proportion of institutions with large default impact.
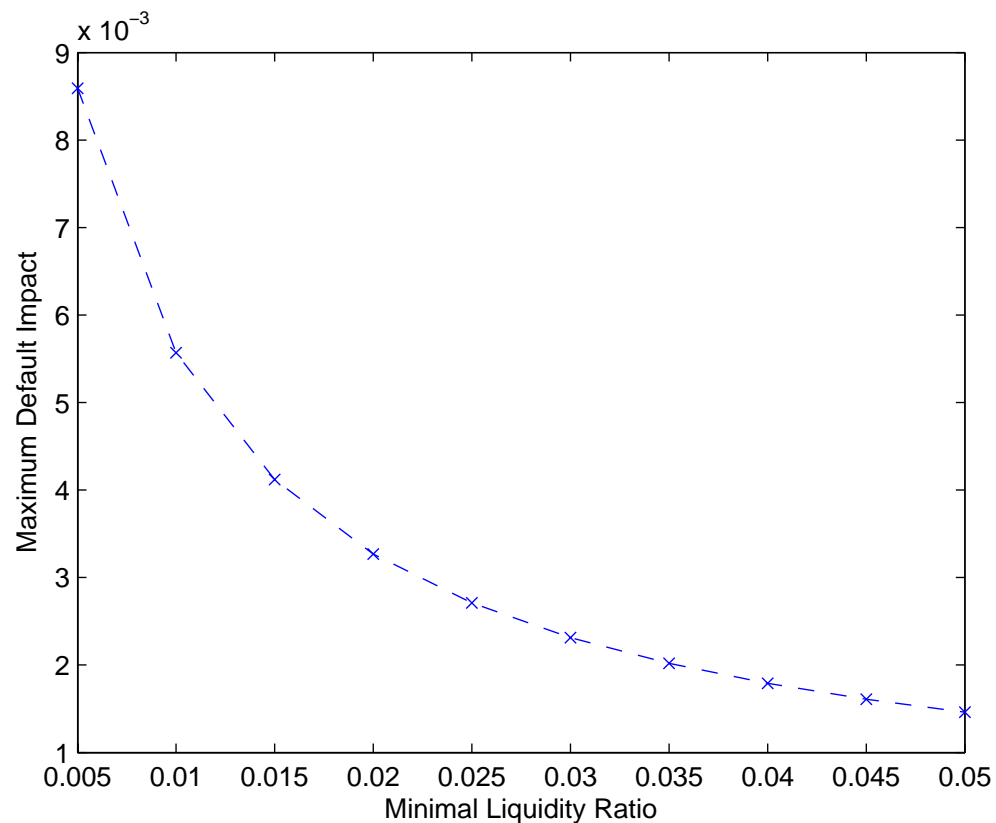
Figure 13: **Worst-case default impact decreases monotonically with the liquidity ratio**: loss generated by the institution with highest default impact as a function of the ratio of liquid reserves to interbank liabilities.

Targeted capital requirements: does one size fit all?

Idea: impose higher capital requirements on institutions whose position in the network may then reinforce more efficiently the network's resilience to contagion.

Analogy with targeted immunization policies in vaccination against epidemics.

Targeted vs non-targeted capital requirements: 5% Tail Conditional Expectation of Systemic Risk Index when (a) imposing a floor on the capital ratio for all institutions, (b) imposing a floor on the capital ratio only for the creditors of the 5% most systemic institutions.
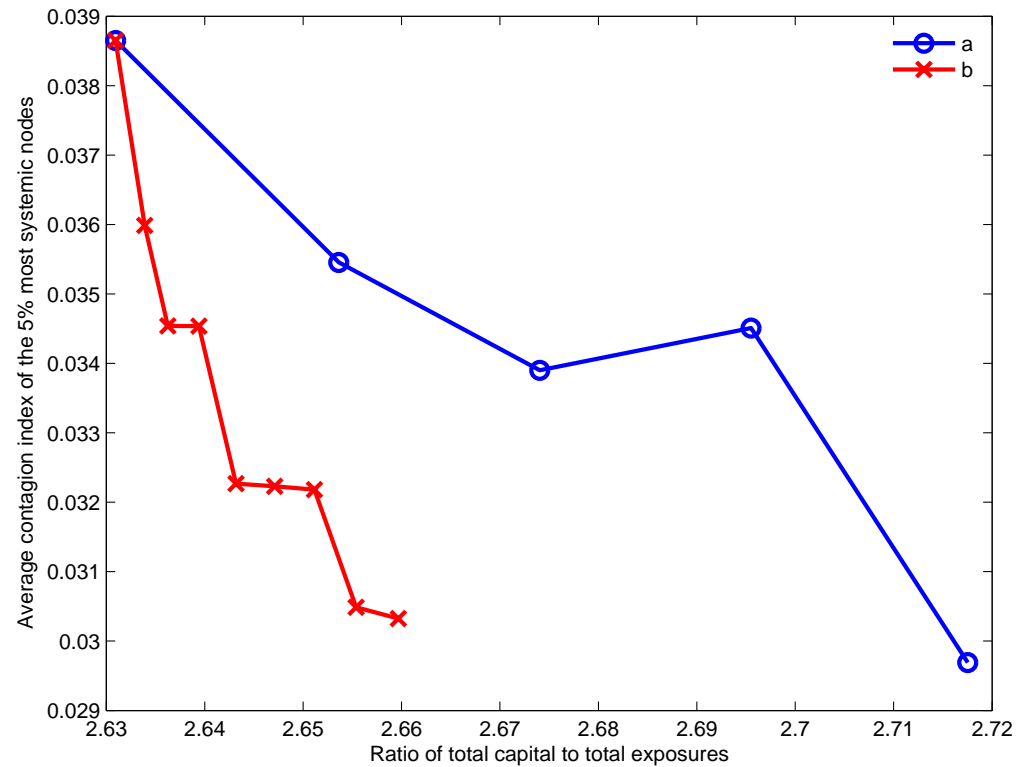
Figure 14: Targeted vs non-targeted capital requirements: 5% Tail Conditional Expectation of Systemic Risk Index when (a) imposing a floor on the capital ratio for all institutions, (b) imposing a floor on the capital ratio only for the creditors of the 5% most systemic institutions.

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 E_{BC} by an equivalent exposure E_{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.

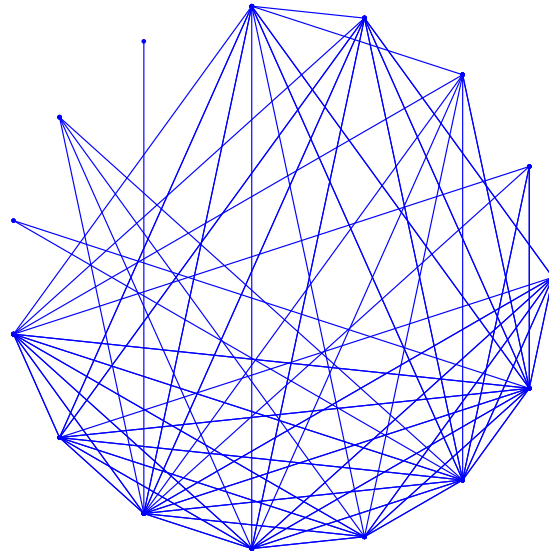- Once the CDS are triggered the network behaves like a "small world".

Figure 15: Dealer to dealer network: the 15 largest CDS dealers represent an almost complete network representing 61 % in terms of outstanding CDS notional
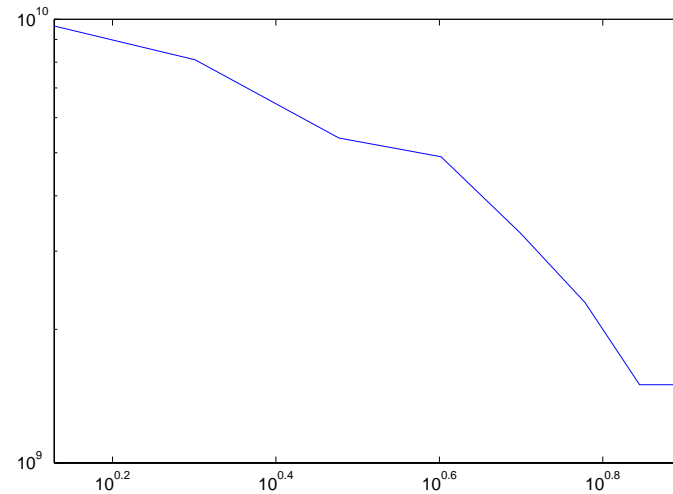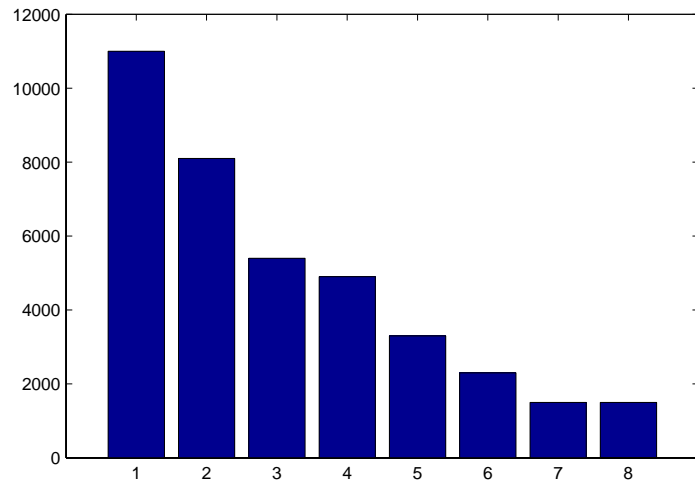
Figure 16: Rank diagram of largest CDS exposures of AIG in Sept 2008 exhibits an exponential tail.
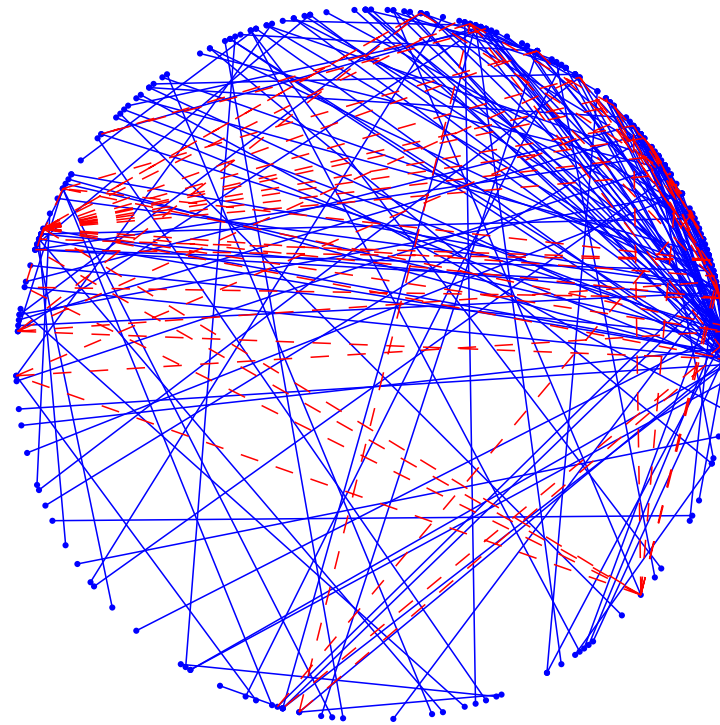
Figure 17: Default of a firm on which a lot of CDS protection has been sold can strongly affect exposures across the network. Blue: counterparty relations. Red: counterparty CDS exposures resulting from the default of a large name.
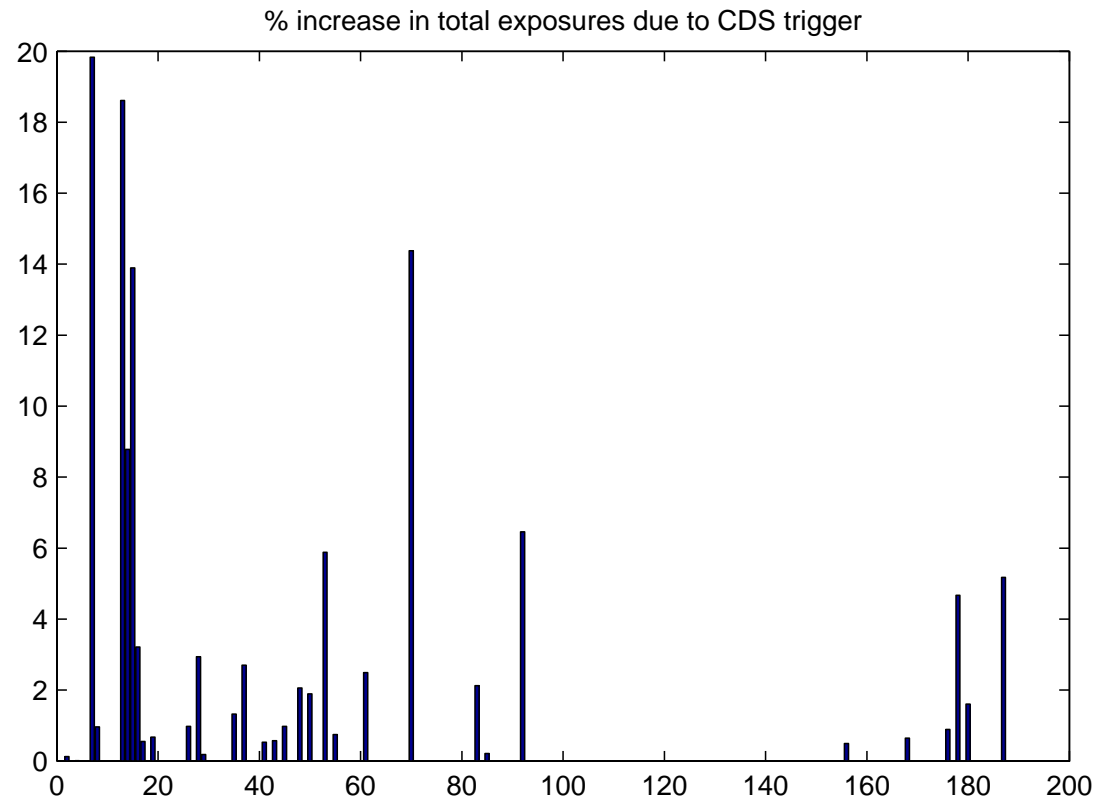
% increase in total exposures due to CDS trigger

Figure 18: 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:
  $c_i \rightarrow c_i - N_{ij}(1 - R)$
  If $c_i < N_{ij}(1 - R)$, the protection seller defaults.

Do credit default swaps increase or decrease systemic risk?
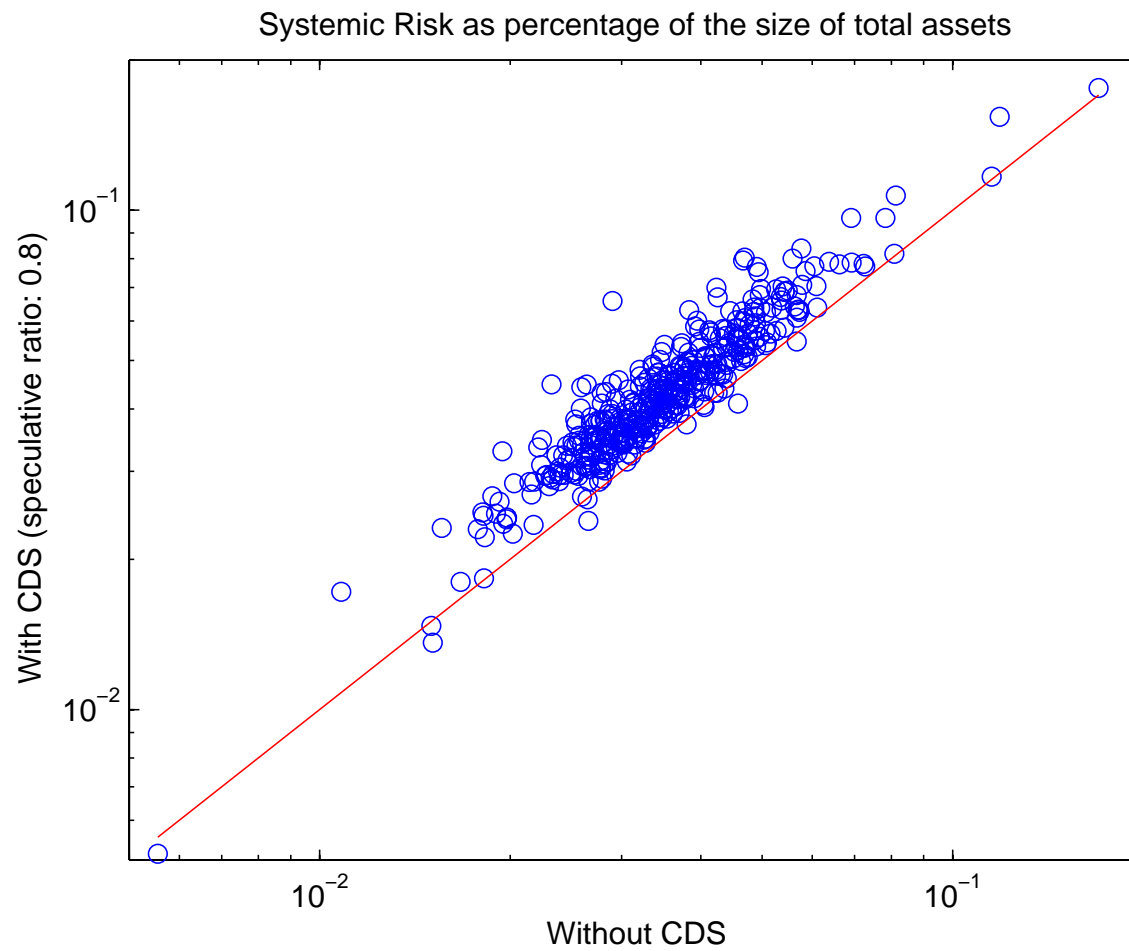
Figure 19: Effect of CDS on systemic risk index: total CDS notional = 20% of balance sheet sizes, 50% of CDS are speculative.
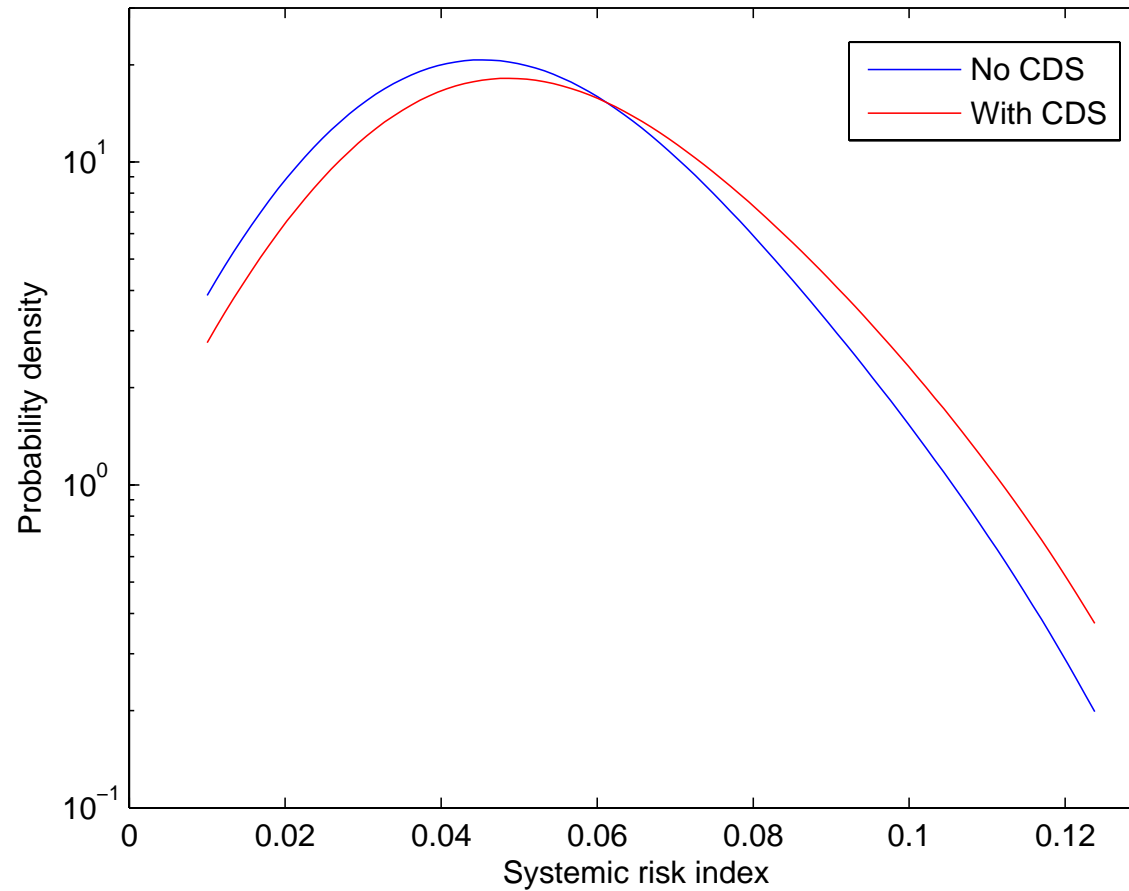
Figure 20: Effect of CDS on probability density of systemic risk index (kernel estimator): total CDS notional = 20% of balance sheet sizes, 50% of CDS are speculative.
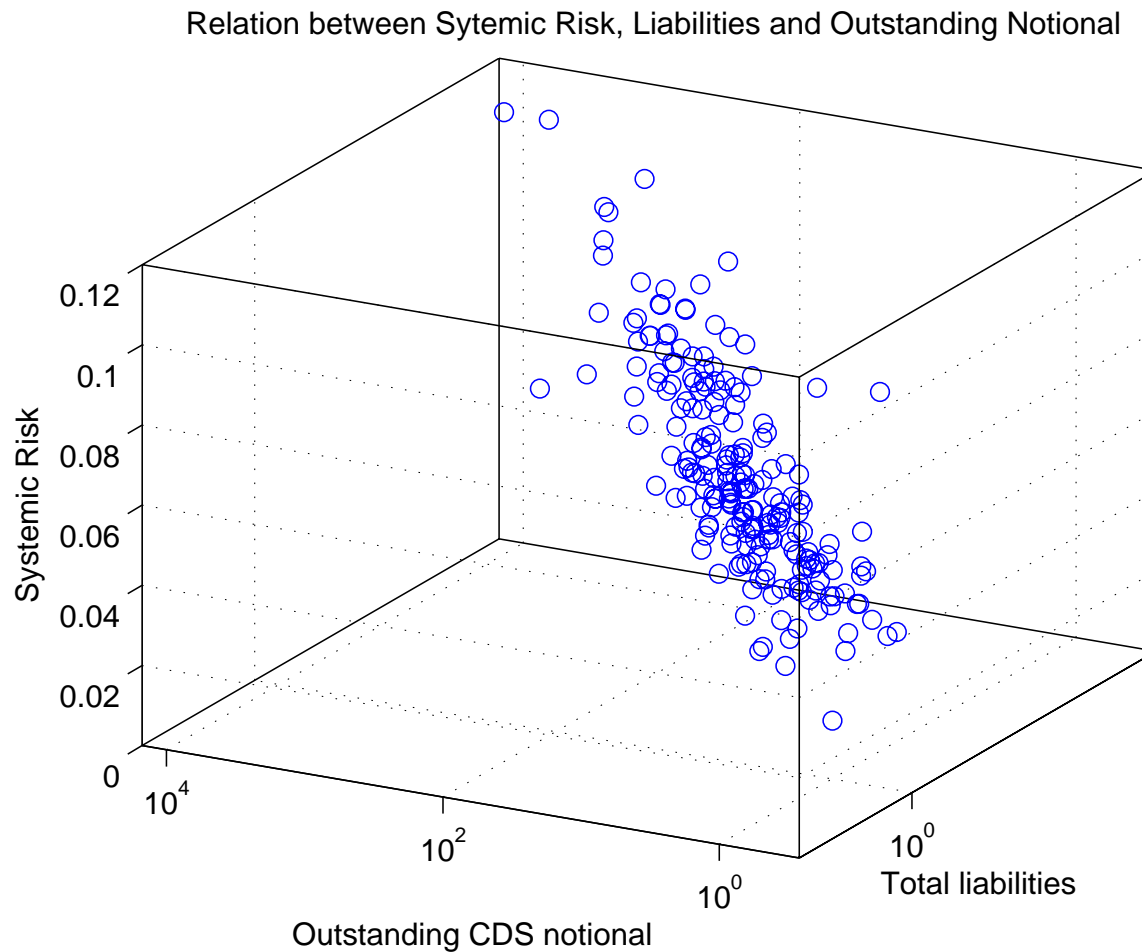
Figure 21: Names on which a large notional of CDS has been written can have a large systemic risk index as a result of the introduction of CDS markets.

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 CCP 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.
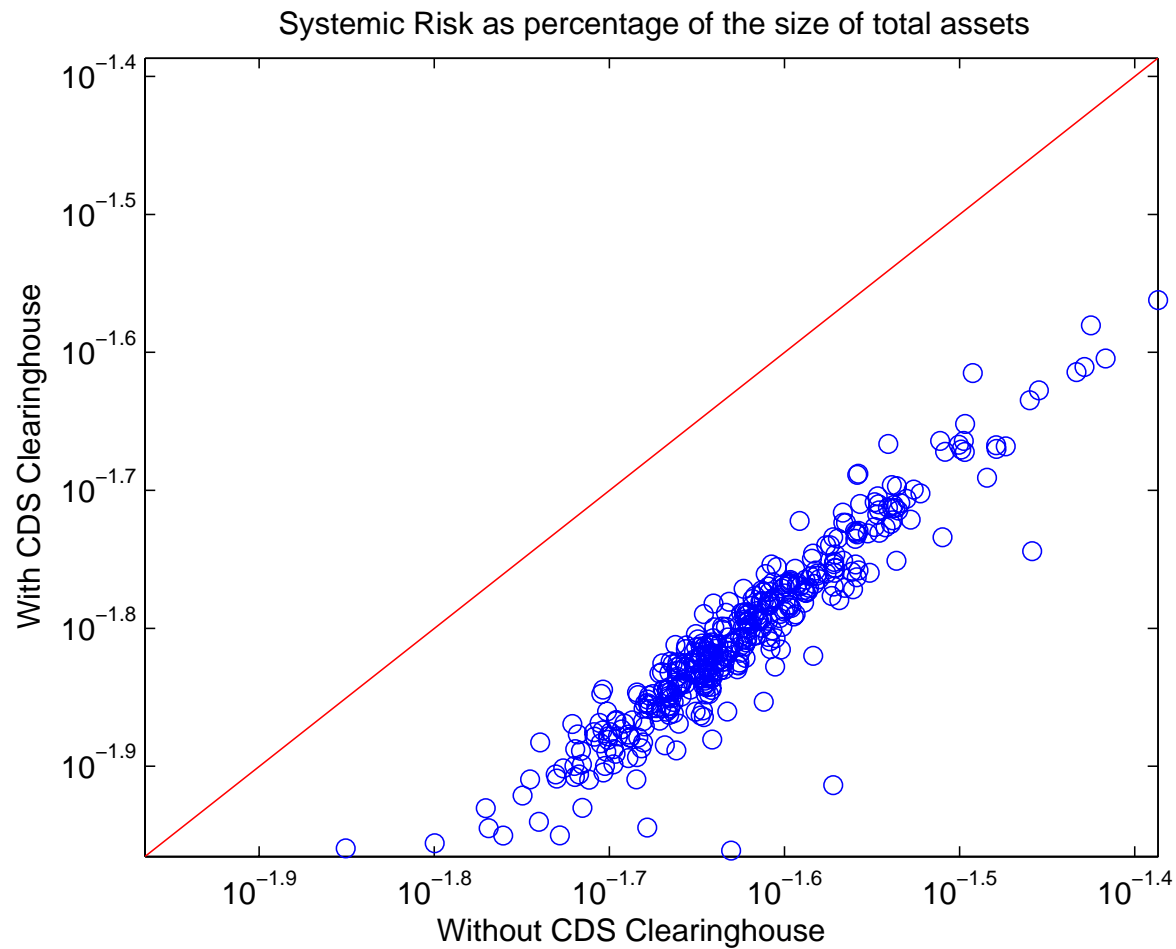
Figure 22: The Clearinghouse effect: Impact of a central counter-party on systemic risk index of financial institutions.
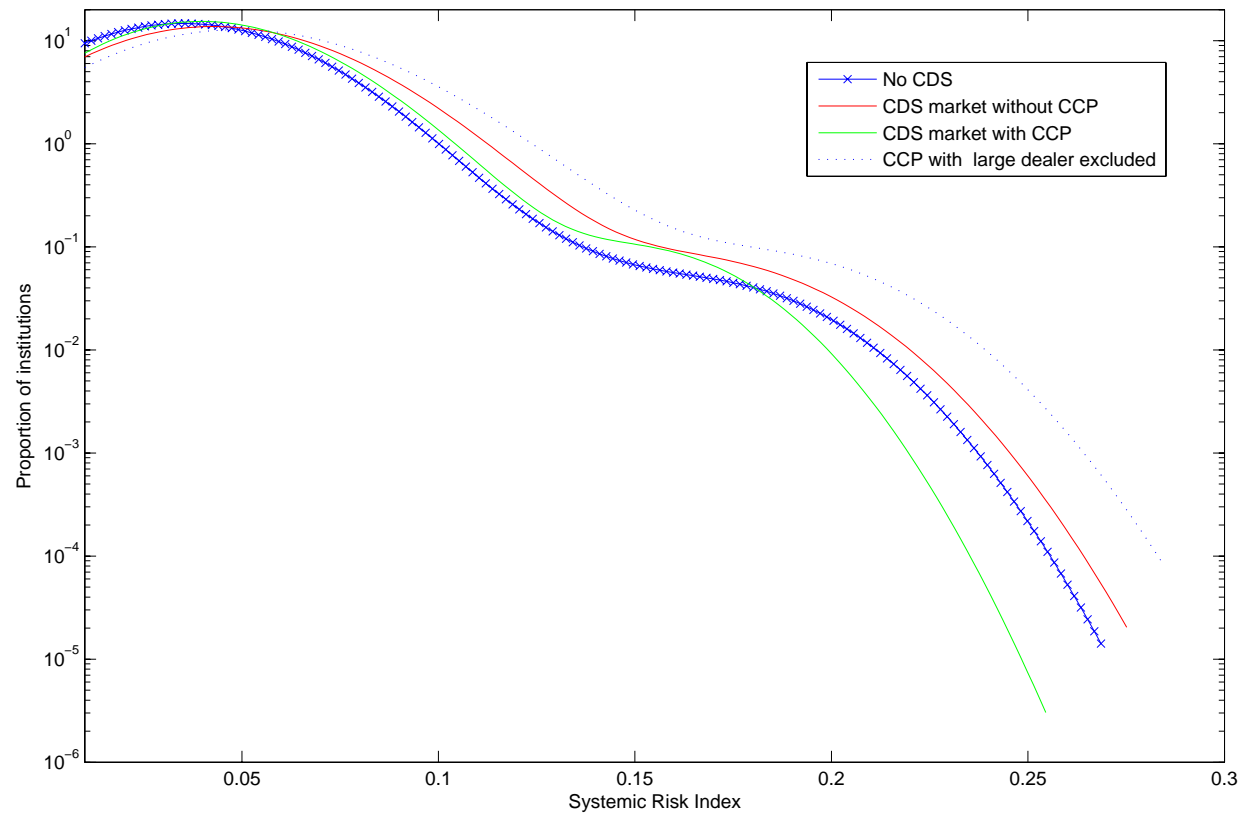
Figure 23: Impact of a central CDS clearinghouse on the distribution of the systemic risk index across institutions.

Implications for data collection

- Network analysis points to the importance (for regulators) of observing *counterparty exposures*

- The example of Brazil shows the feasability of collecting such data.

- In many countries, exposures larger than a threshold are required to be reported. Our analysis suggest that the relevant threshold should be based on a ratio of the exposure to the capital, not

- Derivatives exposures (in particular credit derivatives positions) should be reported in more detail (not aggregated mark-to-market value) -notional, underlying, maturity,..- to enable liquidity stress tests of scenarios where margin calls or derivative payoffs re triggered.

- In all countries banks and various financial institutions are

required already to report risk measures (VaR, etc.) on a periodical basis to the regulators.

- Our approach would require these risk figures to be a *disaggregated* across large counterparties: banks would report a figure for exposures to each large counterparty.

- Large financial institutions *already* compute such exposures on a regular basis so requiring them to be reported is not likely to cause a major technological obstacle.

- In principle *any* counterparty is relevant, not just banks.

- On the other hand, only the largest exposures of an institution come into play.

(Some) Conclusions

- Mapping exposure networks gives valuable insight to regulators on contagion risk and systemic risk. Exposures represent potential future losses and provide information from different market-based indicators.

- 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 $S(i)$.

- Our methodology can be useful for incorporating network effects into stress tests of default and counterparty risk.

- 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 ratios, as opposed to risk-weighted capital ratios, seem to be a key determinant of contagion risk.

- Imposing a minimal capital ratio or a maximal exposure ratio -even if restricted to most systemic nodes- is an effective mechanism for reducing default contagion and the probability of large systemic losses.

- Balance sheet size alone is not the right criterion for determining systemic importance: position in the network and susceptibility/size of counterparties is crucial.

- A node whose counterparties are large, leveraged have high susceptibility to its default will have a high systemic risk index.

- 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.

- 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 a meaningful cost/benefit analysis of

  - the impact of macroprudential regulation on contagion risk
  - 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.

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