Size, Interconnectedness and the Regulation of Systemic Risk

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[1] The opinions expressed in this presentation are those of the authors and are not meant to represent the opinions or official positions of Amundi Asset Management.

Interconnectedness & the example of the GFC

The Global Financial Crisis:

- Subprime crisis $\Leftrightarrow$ banks (credit risk)
- Banks $\Leftrightarrow$ asset management, e.g. hedge funds (funding & leverage risk)
- Asset management $\Leftrightarrow$ equity market (liquidity risk)
- Equity market $\Leftrightarrow$ banks (asset-price & collateral risk)

Two main lessons

- The equity market is the ultimate liquidity provider:

$$\text{GFC} \gg \text{internet bubble}$$

- Lehman default $\gg$ subprime crisis

Supervisory policy responses

- FSB & SIFI (G-SIB, G-SII, NBNI-SIFI)
- Dodd-Frank, Basel III, Volckler rule, TLAC, etc.

Size & systemic risk identification

Table: Average rank correlation (in %) between the five categories for the G-SIBs as of End 2013

		(1)	(2)	(3)	(4)	(5)
(1)	Size	100.0				
(2)	Interconnectedness	94.6	100.0			
(3)	Substitutability	77.7	63.3	100.0		
(4)	Complexity	91.5	94.5	70.1	100.0	
(5)	Cross-activity	91.4	90.6	84.2	95.2	100.0

Source: Roncalli & Weisang (2015).

⇒ We can define G-SIBs by only considering the size category[2].

[2]We don't have the same ranking, but the final list is approximately the same list, which is obtained with the five categories.

The case of asset management

2nd FSB-IOSCO consultation paper (March 2015)

- Goal: Identify Non-Bank Non-Insurance Systemically Important Financial Institutions (NBNI SIFIs)
- Materiality threshold for investment funds: net AUM $\geq$ \$100 bn

Fund	AUM	Asset class Equity	Bond	Diversified
Vanguard Total Stock Market Index Fund	406.5	✓		
Vanguard Five Hundred Index Fund	209.4	✓		
Vanguard Institutional Index Fund	195.5	✓		
Vanguard Total Intl Stock Index Fund	162.5	✓		
American Funds Growth Fund of America	149.4	✓		
Vanguard Total Bond Market Index Fund	144.6		✓	
American Funds Europacific Growth Fund	133.5	✓		
PIMCO Total Return Fund	117.3		✓	
TianHong Income Box Money Market Fund	114.8			
Fidelity® Contrafund® Fund	110.6	✓		
American Funds Capital Income Builder	100.7			(80 / 20)
American Funds Income Fund of America	99.7			(80 / 20)
Vanguard Total Bond Market II Index Fund	93.4		✓	
Franklin Income Fund	92.4			(50 / 50)
American Funds Capital World G&I Fund	91.0	✓		
Vanguard Wellington™	90.7			(60 / 40)
Fidelity Spartan® 500 Index Fund	90.0	✓		
American Funds American Balanced Fund	83.0			(60 / 40)

Source: Morningstar's database, May 5, 2015.

Systemic risk models

The loss of the system is equal to $L(w) = \sum_{i=1}^{n} w_i L_i$, where w_i is the exposure of the system to Institution i.

- SES of Acharya *et al.* (2010):

$$\boxed{\mathrm{SES}_i = w_i \times \mathrm{MES}_i}$$

  where:

$$\mathrm{MES}_i = \frac{\partial\, \mathrm{ES}_\alpha(w)}{\partial\, w_i} = \mathbb{E}\left[L_i \mid L \geq \mathrm{VaR}_\alpha(w)\right]$$

- Delta-CoVaR of Adrian and Brunnermeier (2015):

$$\boxed{\Delta\,\mathrm{CoVaR}_i = \mathrm{CoVaR}_i(\mathscr{D}_i = 1) - \mathrm{CoVaR}_i(\mathscr{D}_i = 0)}$$

  where $\mathscr{D}_i$ indicates if the institution is in distressed situation or not, and:

$$\Pr\{L(w) \geq \mathrm{CoVaR}_i(\mathscr{E}_i)\} = \alpha$$

- SRISK of Acharya *at al.* (2012), which is a new version of SES (`http://vlab.stern.nyu.edu/`)

The Gaussian Case

If $(L_1, \ldots, L_n) \sim \mathcal{N}(\mu, \Sigma)$, we have:

$$\boxed{\mathrm{MES}_i = \mu_i + \beta_i(w) \times (\mathrm{ES}_\alpha(w) - \mathbb{E}(L))}$$

where $\beta_i(w)$ is the beta of the institution loss with respect to the total loss:

$$\beta_i(w) = \frac{\mathrm{cov}(L, L_i)}{\sigma^2(L)} = \frac{(\Sigma w)_i}{w^\top \Sigma w}$$

and:

$$\boxed{\Delta \mathrm{CoVaR}_i = \beta_i(w) \times \frac{\Phi^{-1}(\alpha) \times \sigma^2(L)}{\sigma_i}}$$

In practice, the systemic measures SES, Delta-CoVaR and SRISK are estimated using asset returns $\Rightarrow$ CAPM (size $\times$ market beta).

How to estimate the stressed beta?

The copula approach (SES)

Let **C** be a copula function such that the following limit exists:

$$\lambda^{+} = \lim_{u \to 1^{-}} \frac{1 - 2u + \mathbf{C}(u, u)}{1 - u}$$

Then, **C** has an upper tail dependence when $\lambda^{+} > 0$.

The quantile regression approach (CoVaR)

We have:

$$\Pr\{L_i \leq \beta L \mid L = \mathbb{S}\} = \alpha$$

β is estimated using a non-parametric approach ($\alpha = 99\%$) or a non-Gaussian parametric approach ($\alpha > 99\%$).

$\Rightarrow$ Estimation is related to EVT (extreme value theory).

Systemic risk versus systematic risk

CAPM

We have:

$$\mathbb{E}[R_i] - r = \beta_i \left(\mathbb{E}\left[R^{\mathrm{mkt}}\right] - r\right)$$

where R_i and R^{mkt} are the asset and market returns, r is the risk-free rate and the coefficient β_i is the beta of the asset i with respect to the market portfolio. In this framework, we obtain the one-factor model:

$$R_i = \alpha_i + \beta_i R^{\mathrm{mkt}} + \varepsilon_i$$

where ε_i is a new parametrization of the idiosyncratic risk.

$\Rightarrow$ CAPM & 2^{nd} FSB-IOSCO consultation paper

The dependence issue

Systemic risk = systematic risk (CAPM)

A **stress** $\mathbb{S}$ can only be transmitted to the system by a shock on the systematic component:

$$\begin{aligned} \mathbb{S}\left(R^{\mathrm{mkt}}\right) &\implies \mathbb{S}(R_1, \ldots, R_n) \\ \mathbb{S}(\varepsilon_i) &\;\not\Longrightarrow \mathbb{S}(R_1, \ldots, R_n) \end{aligned}$$

The myth of idiosyncratic risk

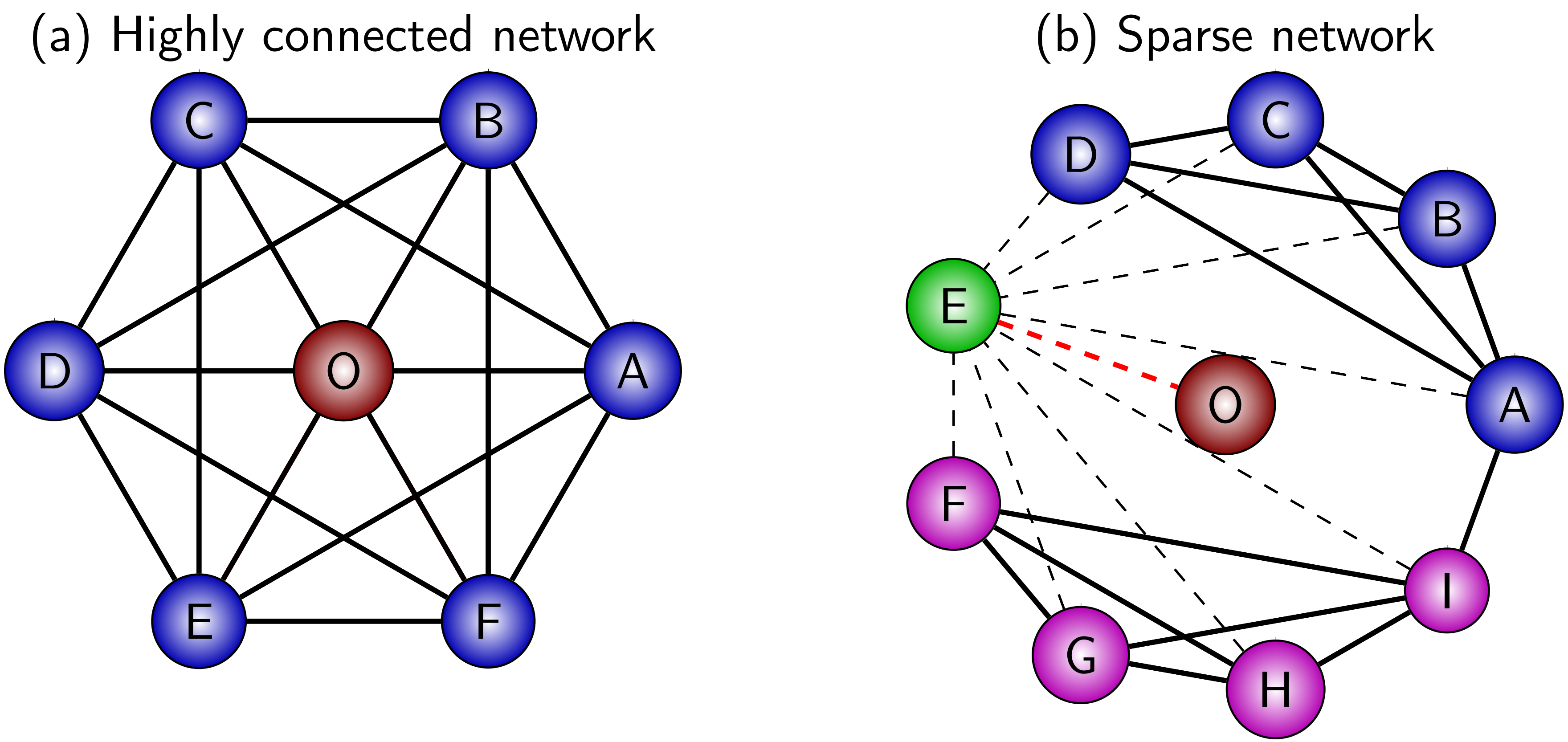
In practice, we can have:

$$\mathbb{S}(\varepsilon_i) \implies \mathbb{S}\left(R^{\mathrm{mkt}}\right) \implies \mathbb{S}(R_1, \ldots, R_n)$$

and:

$$\mathbb{S}(\varepsilon_i) \implies \mathbb{S}(\varepsilon_1, \ldots, \varepsilon_n) \implies \mathbb{S}(R_1, \ldots, R_n)$$

Why LTCM and not Amaranth or Madoff?

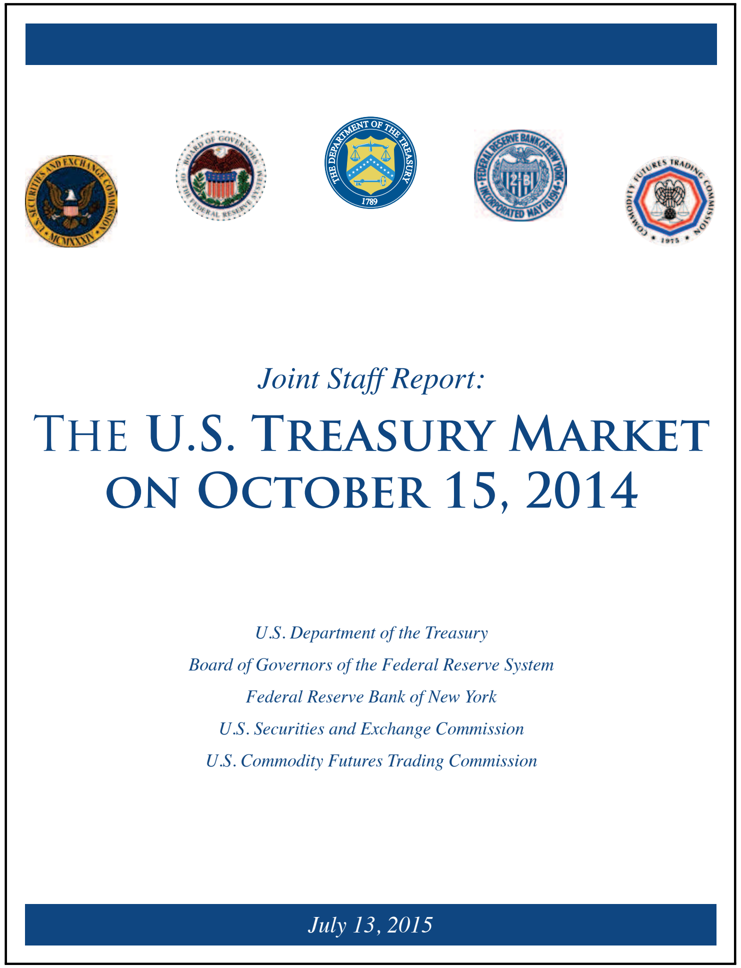


- Madoff: USD 65 BN (Ponzi scheme; no CCR; weakly connected via investors)
- Amaranth: USD 6.5 BN (Gaz futures; low CCR; connected via CCPs)
- LTCM: USD 4.6 BN (IR swaps; high CCR; highly connected via banks)

Examples of network risk

In most models, the origin of a systemic risk is a stress, but...

- August 24, 2015: US ETF Flash Crash
- October 15, 2014: US Treasury Flash Crash
  "*While no single cause is apparent in the data, the analysis thus far does point to a number of findings which, in aggregate, help explain the conditions that likely contributed to the volatility.*"
- May 6, 2010: US Stock Market Flash Crash


Joint Staff Report:

THE U.S. TREASURY MARKET ON OCTOBER 15, 2014

U.S. Department of the Treasury
Board of Governors of the Federal Reserve System
Federal Reserve Bank of New York
U.S. Securities and Exchange Commission
U.S. Commodity Futures Trading Commission

July 13, 2015

Empirical results

Measuring the density of the network (Billio *et al.*, 2012; Cont *et al.*, 2013)

- The goal is to measure the connectivity and the centrality of each node (e.g. institutions)
- What is the contribution of each node to the network density?

Network structure of banking systems

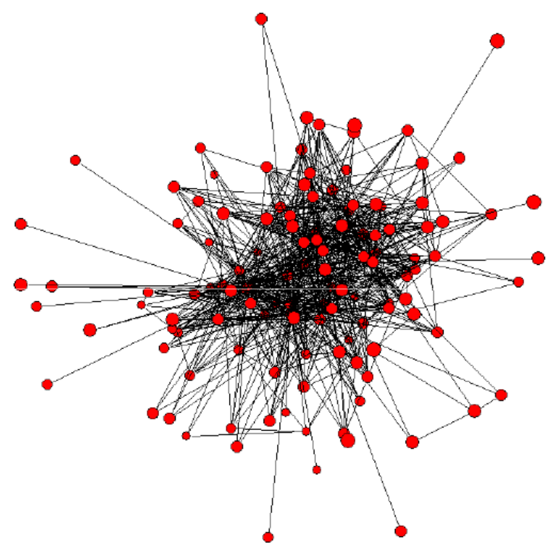


Figure 1: Brazilian financial network (Cont, Moussa & Santos 2009).

The Network Risk

Acemoglu *et al.* (2015)

- Impact of the complexity on the network stability (interbank market)
- If the magnitude and the number of negative shocks are sufficiently small, more complete network enhance the stability of the system
- With more severe shocks, a complete network is more fragile

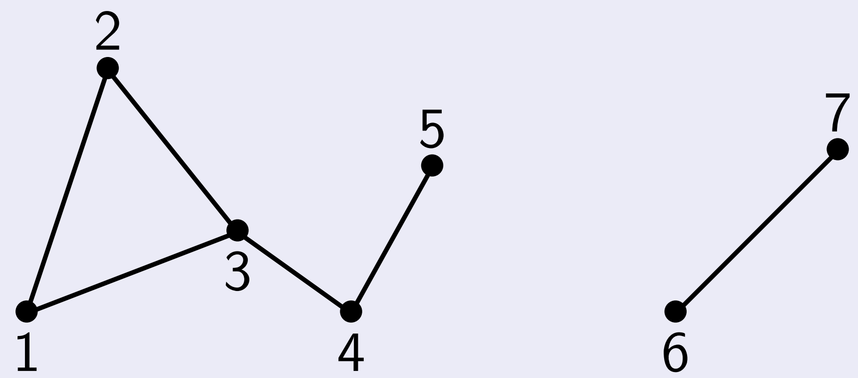
"*Completeness is not a guarantee for stability*"

Interconnectedness vs density

- Network density can enhance financial stability when (external) shocks are small
- Dense interconnections may propagate shocks when (external) shocks are large

Definition of dependency graph

Dependency graph (Erdös-Lovász, 1975)

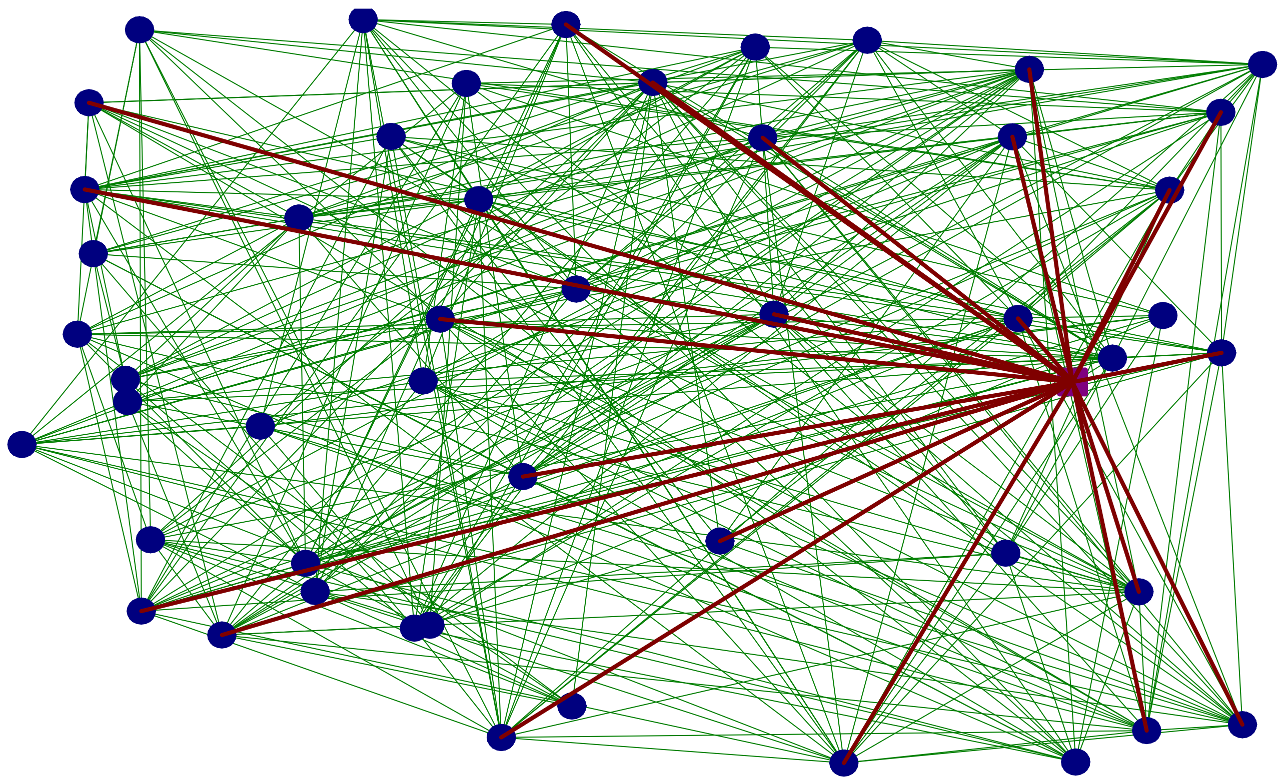


- $(X_1, X_2, X_3, X_4, X_5)$ and (X_6, X_7) are independent;
- (X_1, X_2) and (X_4, X_5) are independent;

Example of dependency graph

- An example with 50 L/S equity hedge funds (including EMN)
- Thresholding approach: $X_i \perp X_j \Leftrightarrow \rho_{i,j} < 30\%$

N = 50 – D = 23 – D/N = 0.46



Application to loss models

- Probabilistic model:

$$L_n = \sum_{k=1}^{n} L_k$$

- Three important quantities:
  1. the number of vertices N
  2. the maximum degree D
  3. the total number of edges $|E|$
- Sparsity:

$$\lim_{n \to \infty} \frac{D_n}{N_n} = 0$$

$\Rightarrow$ CLT with correlated random variables

- Heavy-tailed & skewed distributions

Concentration bounds ($a_k \leq L_k \leq b_k$)

Chernoff inequality

In the i.i.d. case, we have:

$$\Pr\left\{L_n - \mathbb{E}\left[L_n\right] \geq x\right\} \leq \exp\left(\frac{-2x^2}{\sum_{k=1}^n \left(b_k - a_k\right)^2}\right)$$

Jansen inequality

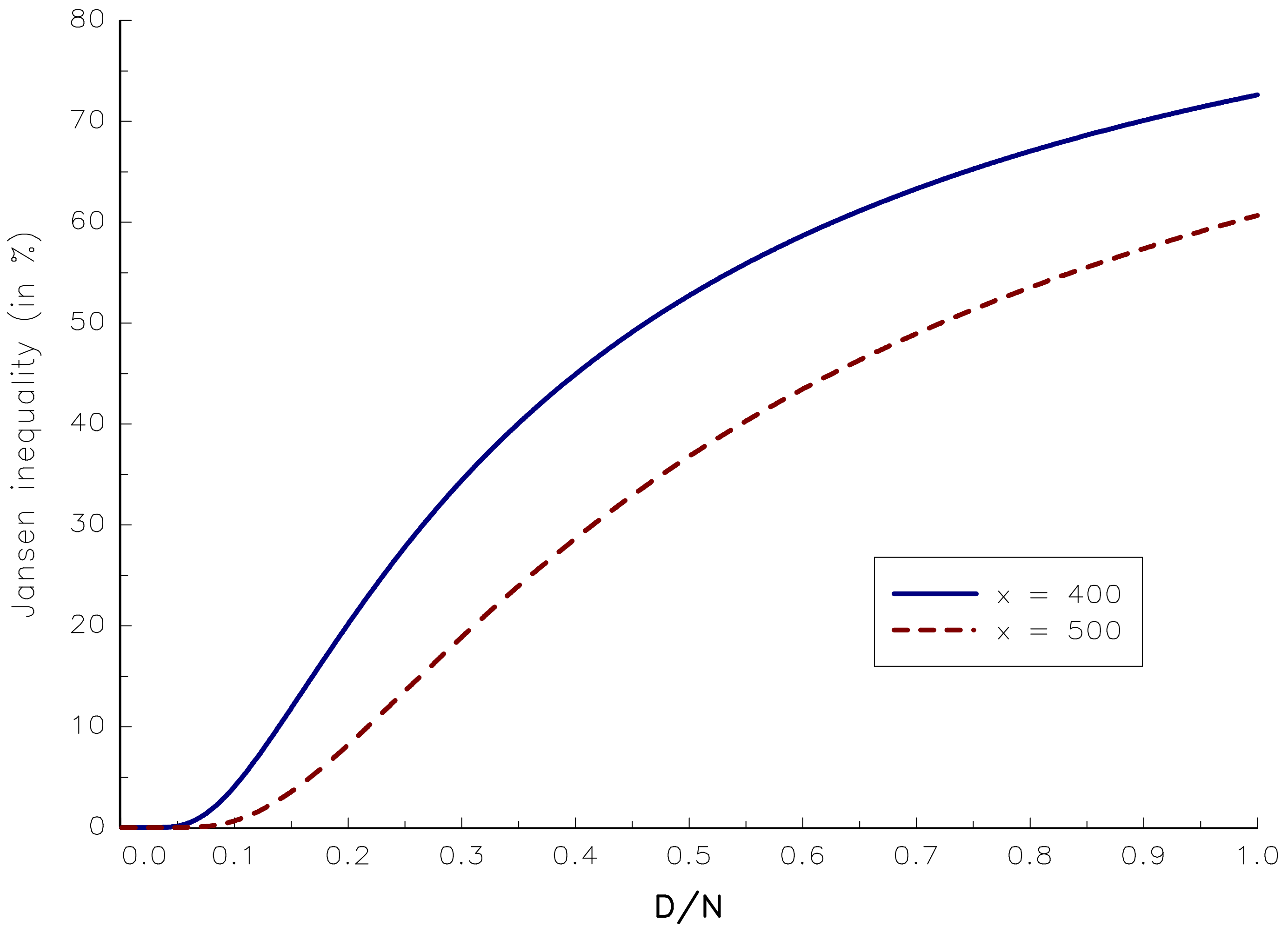
We have:

$$\Pr\left\{L_n - \mathbb{E}\left[L_n\right] \geq x\right\} \leq \exp\left(\frac{-2x^2}{\chi \sum_{k=1}^n \left(b_k - a_k\right)^2}\right) \leq \exp\left(\frac{-2x^2}{D \sum_{k=1}^n \left(b_k - a_k\right)^2}\right)$$

where χ and D are the chromatic number and the maximum degree of the dependency graph.

Illustration

- $N = 1000$, $a_k = 0$ & $b_k = 1$



Dependence can create very large fluctuations!

The dependency graph consists of N/D independent blocks of D vertices. Each block is a complete graph with a constant correlation ρ.

Let $\mathbf{F}^{-1}(\alpha)$ be the quantile α of the loss distribution:

$$\Pr\left\{L_n \geq \mathbf{F}^{-1}(\alpha)\right\} = \alpha$$

We have:

$$\mathbf{F}^{-1}(\alpha) \approx \mathbb{E}[L_n] + q_\alpha \sqrt{1 + \rho D}$$

where q_α is the quantile α of the loss distribution in the Gaussian approximation in the diversified model ($\rho = 0$).

Thresholding approach

If we consider the dependency graph where $\rho \geq \rho^\star > 0$, we obtain:

$$\mathbf{F}^{-1}(\alpha) \approx \mathbb{E}[L_n] + q_\alpha \sqrt{1 + 2\rho^\star \frac{|E|}{n}}$$

Risk contributions

- L = loss of the system
- $L^{(-i)} = L - L_i$ = loss of the system without the entity i
- $L^{(-\mathscr{E})} = L - L_{(\mathscr{E})}$ = loss of the system without the entities $i \in \mathscr{E}$

$\Rightarrow$ Pseudo risk contributions are calculated using the pruning algorithm to determine the main contributor of the systemic loss:

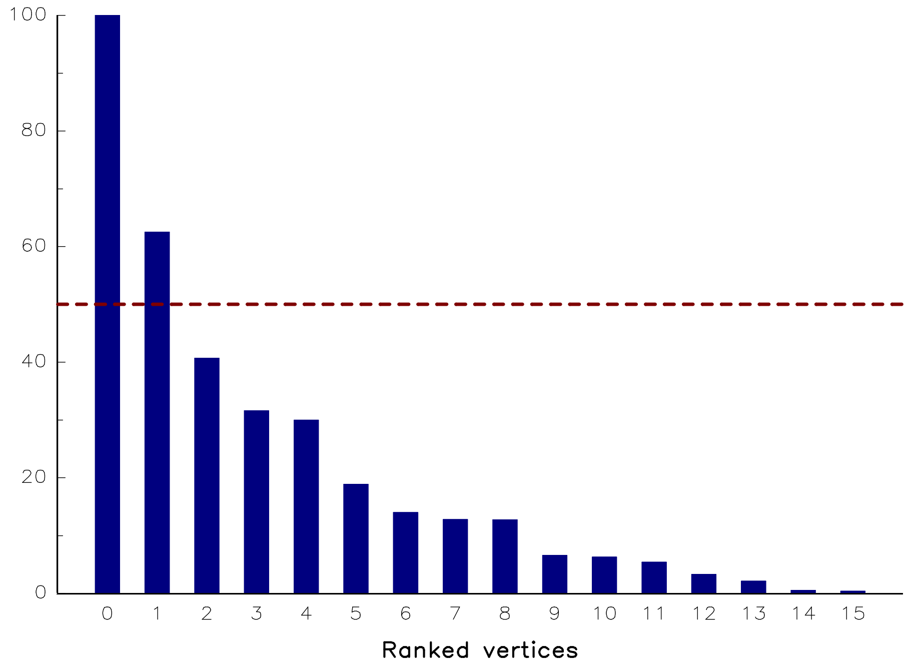
$$\mathscr{E} = \mathscr{E}^{-} \cup \left\{ j \notin \mathscr{E}^{-} : \sup_{i} L - L_{(\mathscr{E}^{-})} - L_i \right\}$$

The idea is to rank the vertices according to these pseudo risk contributions.

Policy implications

Regulation of financial institutions

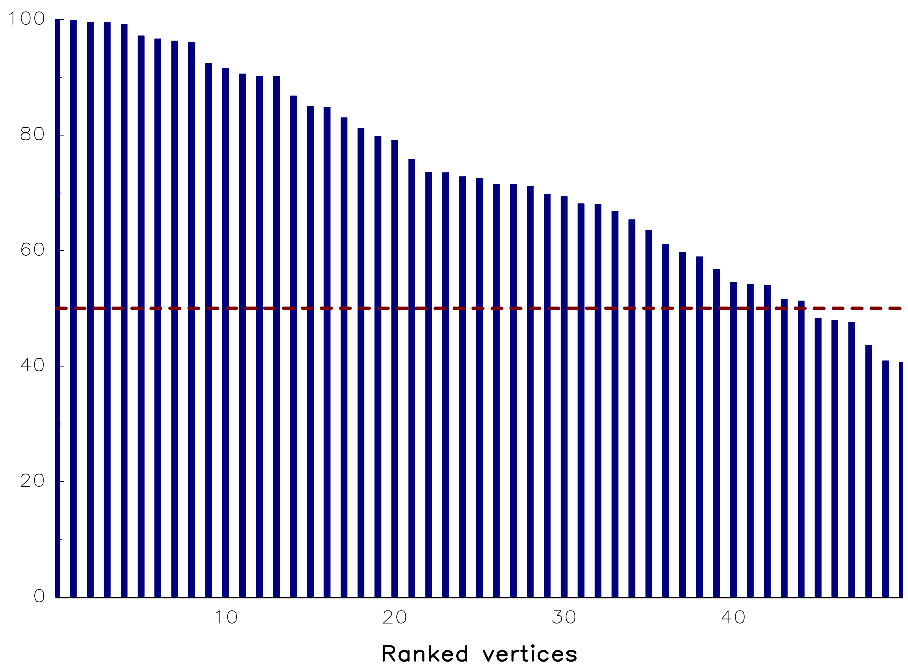
- A sparse network with large contributors
- The entities may be highly connected or not
- The example of hedge funds?



Policy implications

Regulation of the market structure

- Dense network
- Entities are highly connected
- The example of liquidity risk?



An Illustration with Money Market Funds

"Following the bankruptcy of Lehman Brothers in 2008, a well-known fund – the Reserve Primary Fund – suffered a run due to its holdings of Lehman's commercial paper. This run quickly spread to other funds, triggering investors' redemptions of more than USD 300 billion within a few days of Lehman's bankruptcy" (Kacperczyk and Schnabl, 2013).

- Deposit insurance extended to MMFs (September 19, 2008)
- ABCP money market mutual fund liquidity facility (AMLF) between September 2008 and February 2010

Remark

Trouble of small MMFs is a signal to redeem for all the investors in MMFs, whatever the size of the MMF.

Conclusion

- Systemic risk $\neq$ systematic risk
- The impact of idiosyncratic shock depends on the network structure
- The myth of external shocks and stressed scenarios
- In dense networks, interconnectedness is more important than size
- The regulation of market structures is certainly more efficient than SIFI designation in asset management

$$\boxed{\begin{array}{c}\text{Non-banking systemic risk} \neq \text{banking systemic risk} \\ \Downarrow \\ \text{Policy answers must be different}\end{array}}$$

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