# Systemic Risk: the Cross-Section Dimension

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Structured Curriculum Course
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# Outline

# Key Learning Points (1)

- Conceptual Overview
  - Interconnectedness
  - Systemic risk
- From Concept to Practice
  - Direct exposure networks
  - Market-based networks
  - Portfolio Approaches

# Key Learning Points (2)

- What practical people do
  - Indicator approach for G-SIBs
- New directions
  - Systemic communities
  - Agent-based models
- Hands-on exercises
  - Direct exposure networks (Excel)
  - CoVaR - CoRisk calculations
  - Portfolio approach

# Outline

# Interconnectedness and systemic risk

- Structure of financial system
  - Direct exposures
  - Common exposures
- Interconnectedness (cross-section)
  - Contagion and shock amplification
  - Domino effects
  - Adverse spillovers

# Liquidity spiral: a systemic risk manifestation

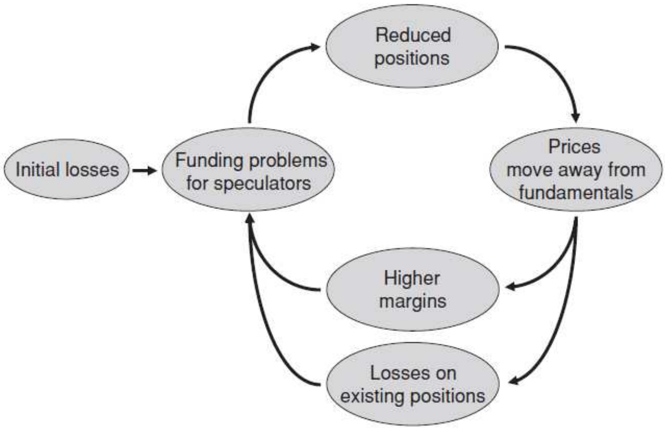



**Figure 2**
**Liquidity spirals**
The figure shows the loss spiral and the margin/haircut spiral.

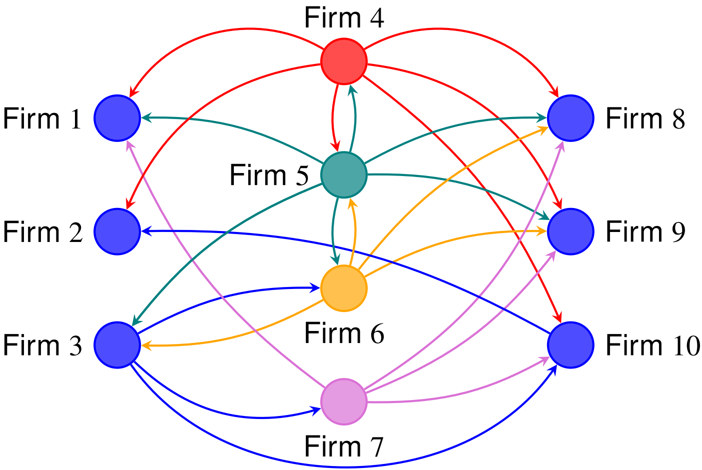
Source: Brunnermeier and Pedersen (2009)

# Financial systems as networks

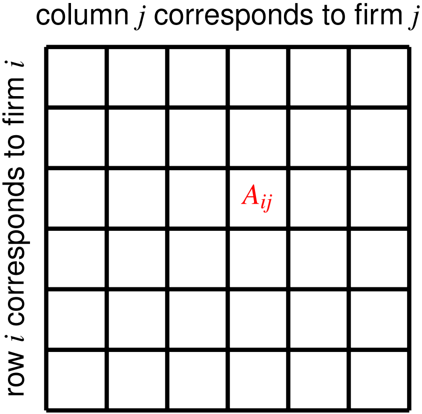
# Network representation

- Networks serve to visualize and to analyze interconnectedness
- Networks has two main elements
  - Nodes (vertices)
  - Edges (links)
- Nodes
  - Firms
  - Markets
  - Risk factors
- Edges
  - Inter-firm loans
  - Security price correlations
  - Spillover measures

# Interfirm exposures (1)

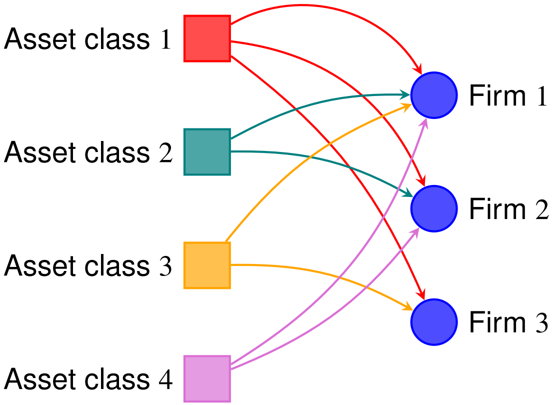


# Interfirm exposures (2)



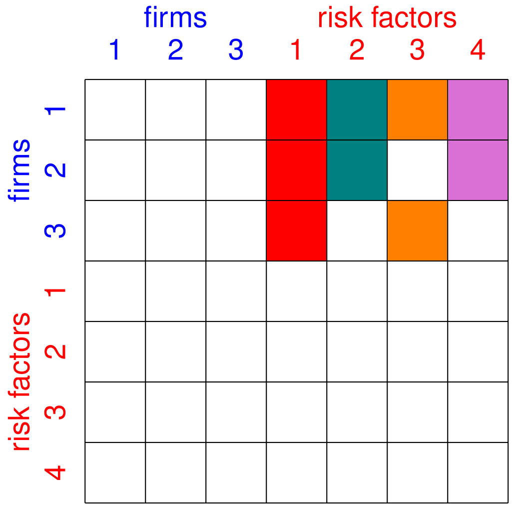

$A_{ij}$ is claim of firm $i$ on firm $j$

# Exposure to common factors (1)

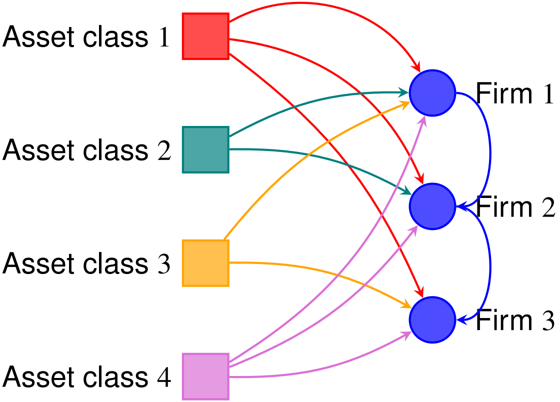



* This is a bipartite network, e.g. Zhao et al (2013)

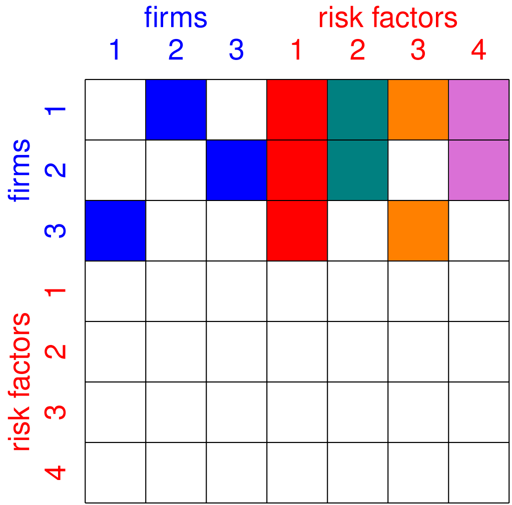
# Exposure to common factors (2)



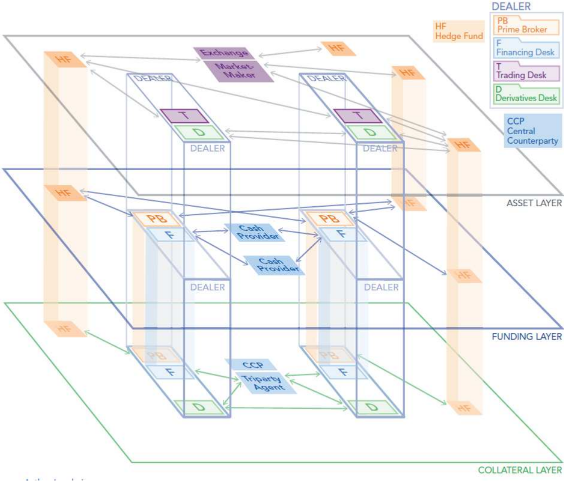
# Interfirm and common factor exposures



# Interfirm and common factors (2)



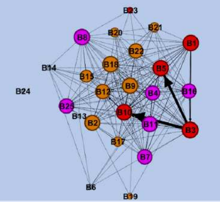
# Multiplex (multi-layer) networks (1)




Source: Bookstaber and Kenett (2016)

# Multiplex (multi-layer) networks (2)

(a) Deposit with Maturity < 1 yr [Asset Type 4-6 in Table 2]

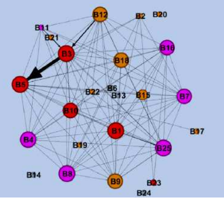



(b) Key network stats

| Key network statistics | |
|---|---|
| Average Degree | 12.4 |
| Network Diameter | 3 |
| Graph Density | 0.517 |
| Avg. Path Length | 1.41 |

Figure 2. Network of Deposit with maturity < 1 yr.

(a) Deposits with maturity > 1 yr [Asset Type 7-9 in Table 2]




(b) Key network stats

| Key network statistics | |
|---|---|
| Average Degree | 6.4 |
| Network Diameter | 3 |
| Graph Density | 0.267 |
| Avg. Path Length | 1.361 |

Source: Sun and Chan-Lau (2017)

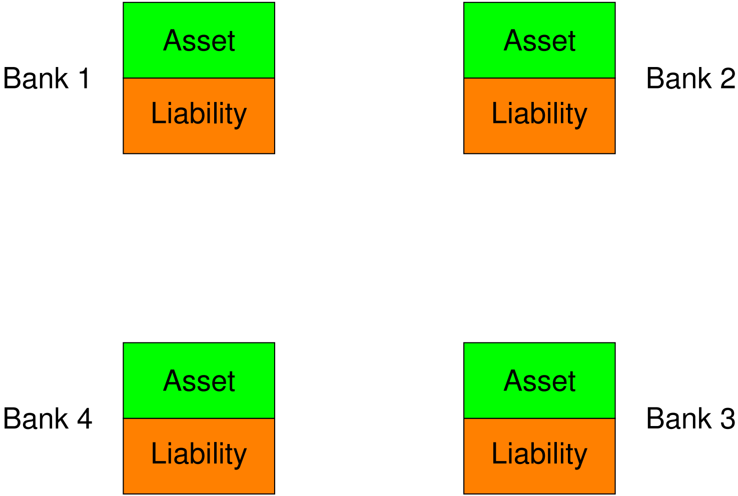
# Outline

# Direct exposure networks

- Network topology
  - Nodes and connecting edges
  - Transmits and amplifies shocks
  - Changes constantly and frequently
  - Dynamics not clearly understood
- Systemic risk analysis
  - Centrality measures
  - Default simulation algorithms
    - Take down one firm (or selected group) at a time
    - Check impact on other firms
    - Repeat cycle in case other firms default

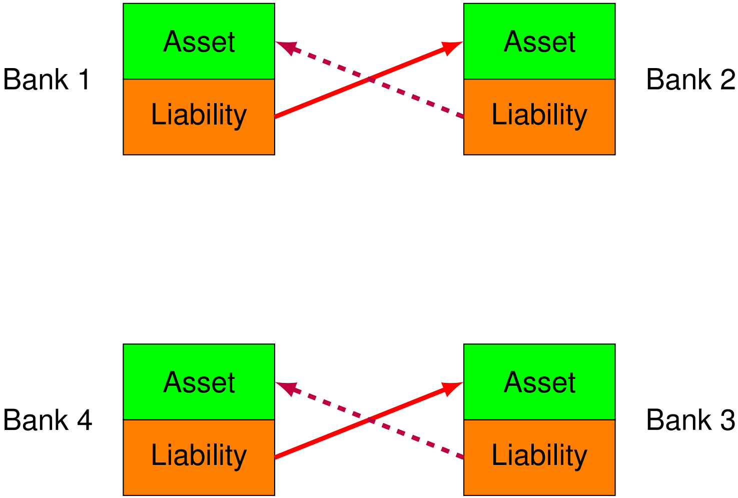
# Why topology matters

# Example 1: No systemic firms



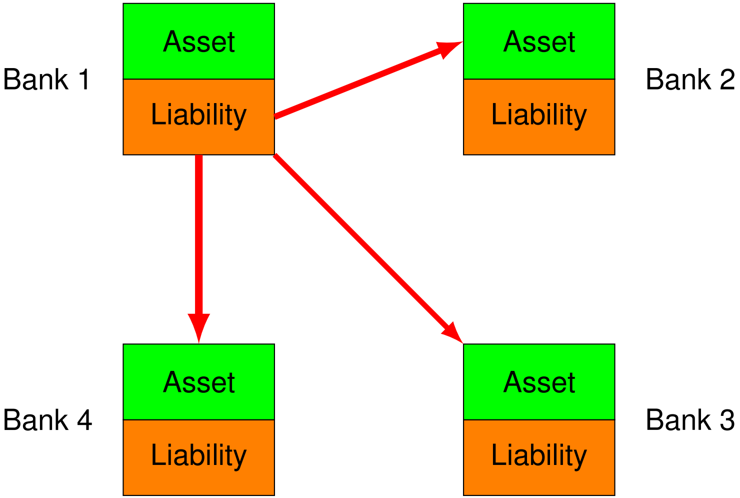

Source: Chan-Lau (2013)

# Example 2: Two systemic sub-systems



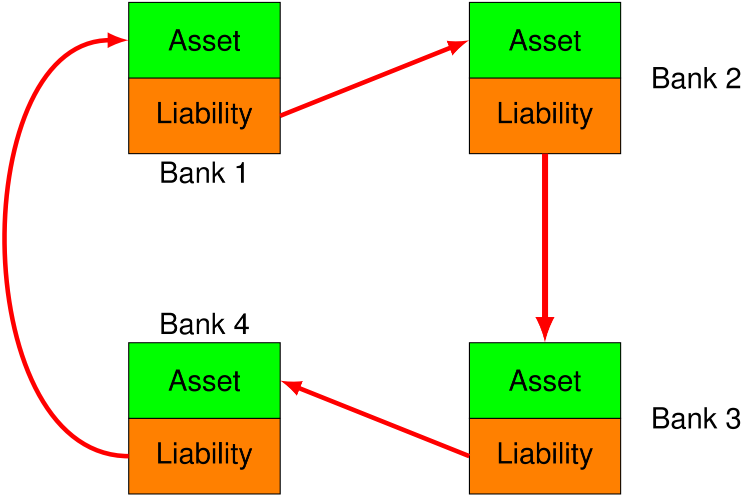

Source: Chan-Lau (2013)

# Example 3: One systemic firm




Source: Chan-Lau (2013)

# Example 4: Every firm is systemic




Source: Chan-Lau (2013)

# Centrality measures

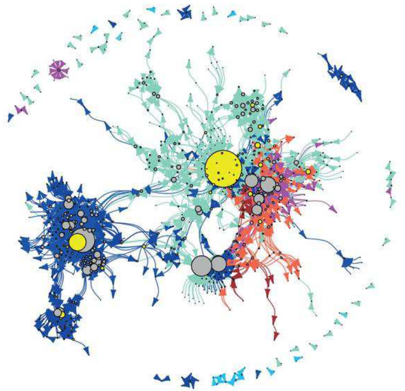
# Centrality measures (1)

Apply to any type of network

- Strength
- Closeness
- Eigenvector centrality
- PageRank

# Centrality measures (2)

1. Wells Fargo model network interconnections



NB, size of circles represents degree of connectedness; coloured lines represent different business lines; arrows represent direction of information flow

Source: Wells Fargo

# Counterfactual default simulations

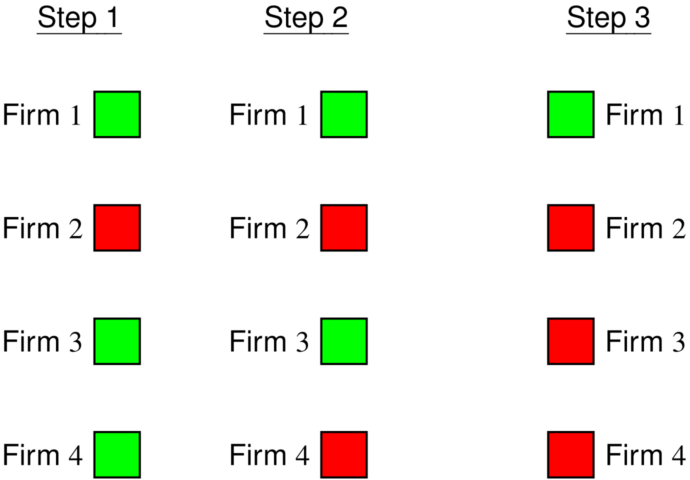
# Default cascade algorithm

Follows groundwork set by Eisenberg and Noe (2001)

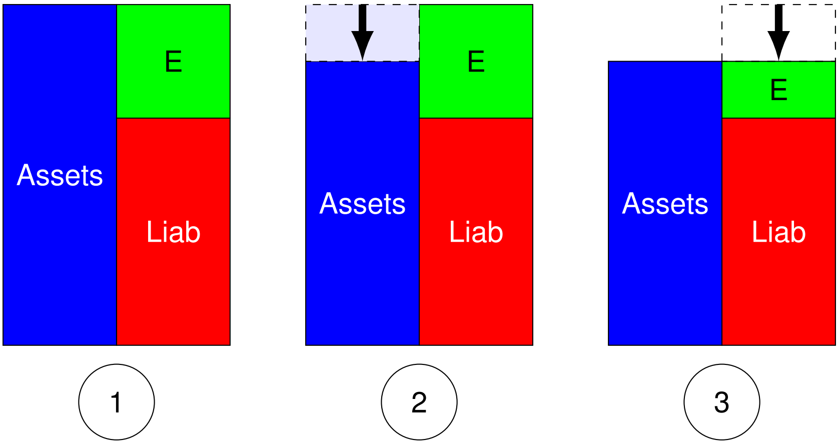
1. Construct matrix of interfirm exposure
2. Firm $i$ fails by assumption
3. Any firm $j$ fails
   - Losses exceed capital
   - Capital falls below threshold
4. Second round of contagion prompted by failure of $j$ firms

Don't forget: it is just a snapshot at time data was collected!

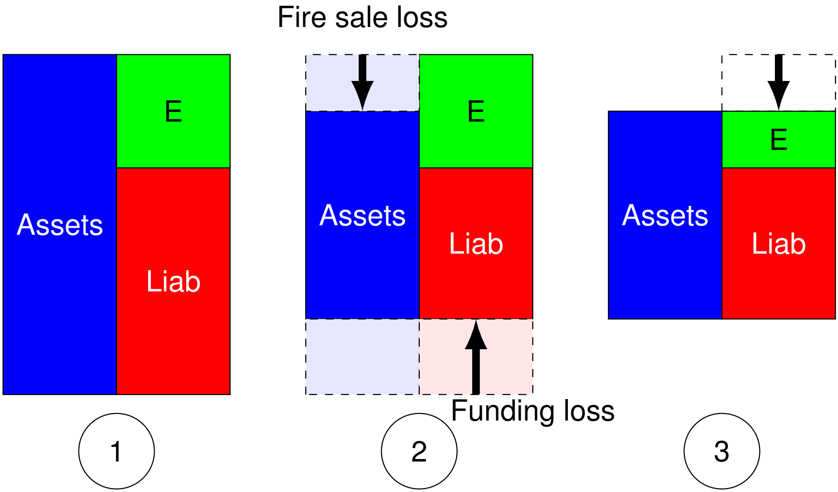
# Default cascade



# Credit shock



# Funding shock



# Hands-On Exercise 1:
# Network analysis in Excel

## Espinosa and Sole (2010)

# Modeling additional second round-effects

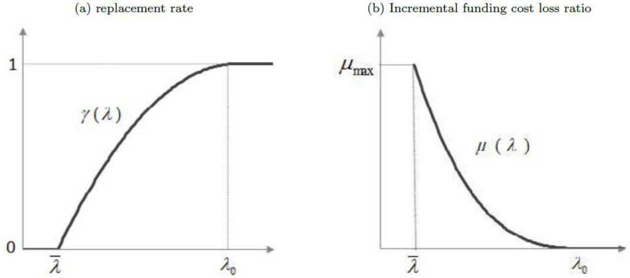
# Additional second-round effects (1)

- Counterfactual simulations
  - Require failure of a firm
  - Shocks work only through inter-firm exposures
  - Nothing happens if no firm defaults

# Additional second round effects (2)

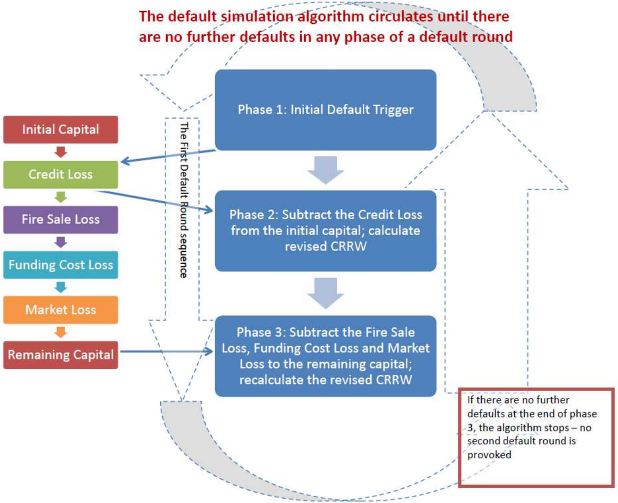
## Funding cost model (Jo, 2012)

- Capital ratios reflect risk of firm
- Higher risk $\Rightarrow$ lower funding replacement rate
- Higher risk $\Rightarrow$ higher funding costs




Source: Jo (2012)

# Additional second round effects (3)




Source: Sun and Chan-Lau (2017)

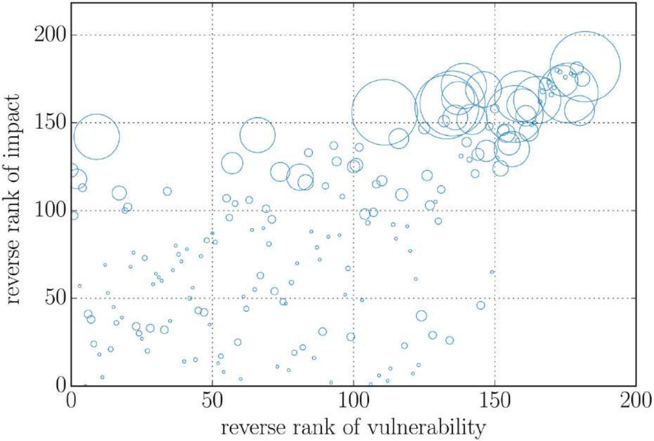
# Additional second round effects (4)

**DebtRank (Bardoscia et al, 2015)**

- Second-round effects from counterparty risk
- Inter-firm exposure reflects changing default risk
- Analogous to counterparty valuation adjustment (CVA)
- The trick
  - Value of claim on firm depends on firms' change in equity value
  - Equity value falls $\Rightarrow$ value on claim falls
- Default is no longer necessary for contagion

# Additional second round effects (5)

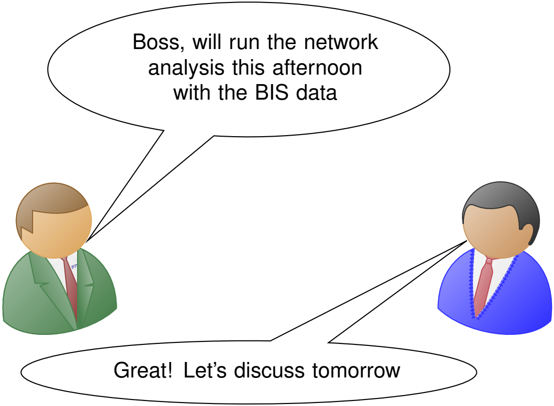
Impact and vulnerability of European banks in 2008, 0.5 percent asset price decline



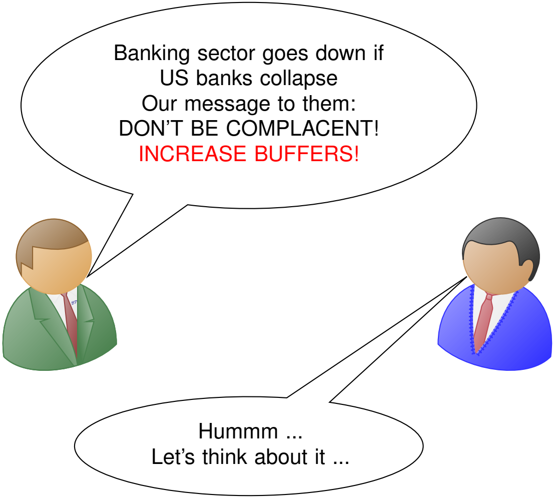

Source: Bardoscia et al (2015)

# Caveats

# Caveats when using BIS banking data (1)



# Caveats when using BIS banking data (2)



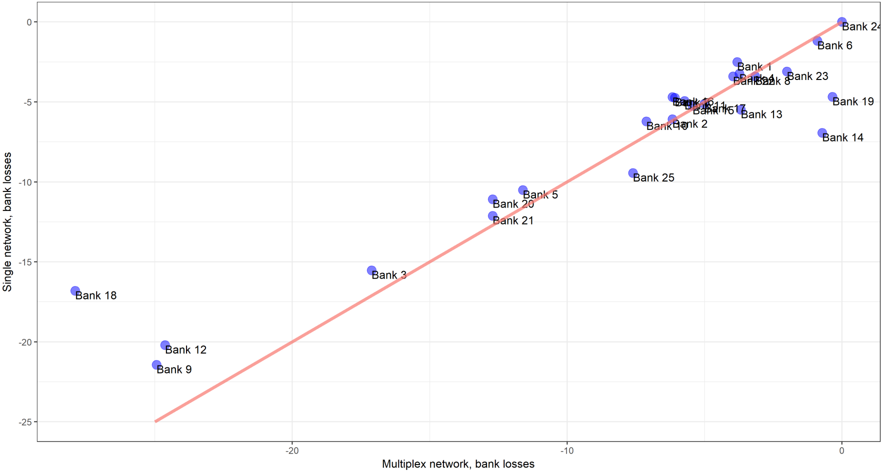
# Multiplex (multi-layer) networks (1)

Table 2. Asset classes, maturity and currency denomination.

| Exposure type | Maturity | Currency of denomination | Type of instruments |
|---|---|---|---|
| 1 | Overnight | Domestic, nominal | Checking accounts, other sight deposits, in-due process |
| 2 | Overnight | Domestic, UF denominated | |
| 3 | Overnight | Foreign currency | |
| 4 | Less or equal to 1 year | Domestic, nominal | Term deposits, in-due-process |
| 5 | Less or equal to 1 year | Domestic, UF denominated | Term deposits, in-due-process |
| 6 | Less or equal to 1 year | Foreign currency | Term deposits, in-due-process |
| 7 | More than 1 year | Domestic, nominal | Term deposits, in-due-process |
| 8 | More than 1 year | Domestic, UF denominated | Term deposits, in-due-process |
| 9 | More than 1 year | Foreign currency | Term deposits, in-due-process |
| 10 | Over night | Domestic, nominal | Repos |
| 11 | Over night | Domestic, UF denominated | Repos |
| 12 | Over night | Foreign currency | Repos |
| 13 | Less or equal to 1 year | Domestic, nominal | Repos |
| 14 | Less or equal to 1 year | Domestic, UF denominated | Repos |
| 15 | Less or equal to 1 year | Foreign currency | Repos |
| 16 | Less or equal to 1 year | Domestic, nominal | Derivatives |
| 17 | Less or equal to 1 year | Domestic, UF denominated | Derivatives |
| 18 | Less or equal to 1 year | Foreign currency | Derivatives |
| 19 | More than 1 year | Domestic, nominal | Derivatives |
| 20 | More than 1 year | Domestic, UF denominated | Derivatives |
| 21 | More than 1 year | Foreign currency | Derivatives |
| 22 | Less or equal to 1 year | Domestic, nominal | Interbank claims |
| 23 | Less or equal to 1 year | Domestic, UF denominated | Interbank claims |
| 24 | Less or equal to 1 year | Foreign currency | Interbank claims |
| 25 | More than 1 year | Domestic, nominal | Interbank claims |
| 26 | More than 1 year | Domestic, UF denominated | Interbank claims |
| 27 | More than 1 year | Foreign currency | Interbank claims |

Source: Sun and Chan-Lau (2017)

# Multiplex (multi-layer) networks (2)




Source: Chan-Lau (2010)

# Outline

# Correlation approaches

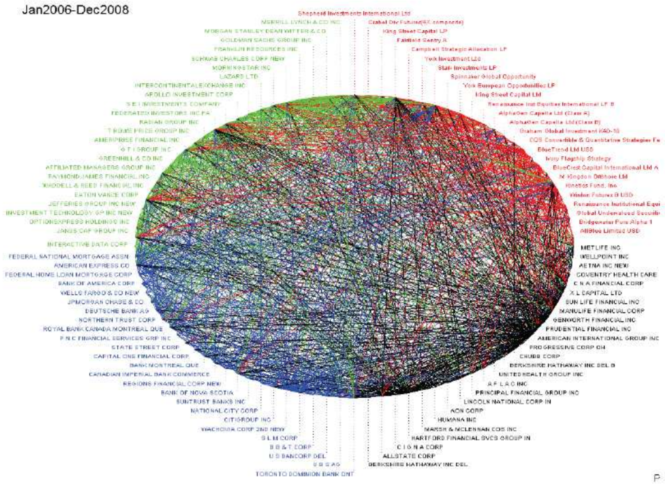
# Correlation approaches (1)

- Basic idea
  - Time series of market prices, i.e. CDS, PDs, equity returns
  - Find correlation-type matrix
  - Matrix defines network
- Systemic risk assessment
  - Centrality measures
- Some issues
  - Plain correlation creates undirected edges
  - Unstable correlation matrix
  - Correlation-based measures may capture third-party effects

# Correlation approaches (2)

- Some solutions
    - Granger-causality networks
    - Partial correlation networks
    - Regularized correlation networks
- Solutions do not apply to multi-layer networks!
    - Ad-hoc methods needed

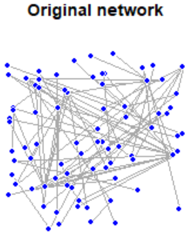
# Granger-Causality network

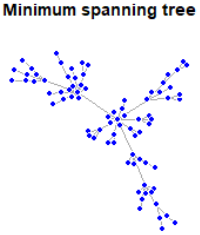



Source: Billio et al (2012)

# Partial correlation network (1)

- Granger causality networks are very dense
- Trim or remove some of the edges
- Potential solution: minimum spanning tree
- But may remove too many edges

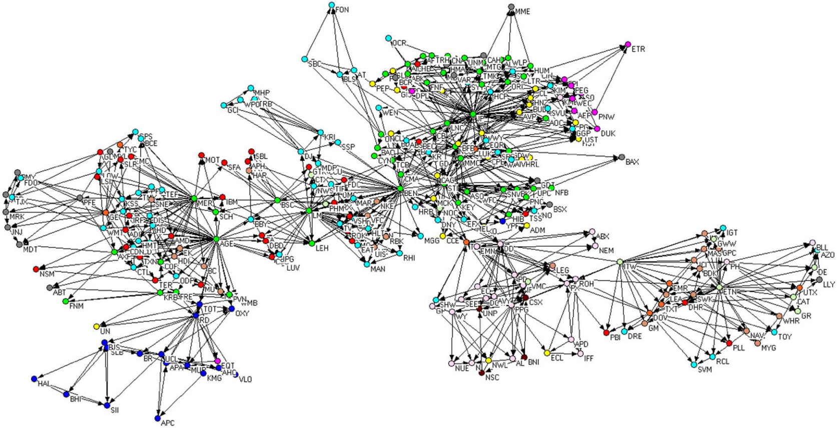


# Partial correlation network (2)

- Firms A, B, and C
- Correlation between A and B due to
  - Correlation between A and C
  - Correlation between B and C
- Partial correlation removes effect of C

# Partial correlation network (3)

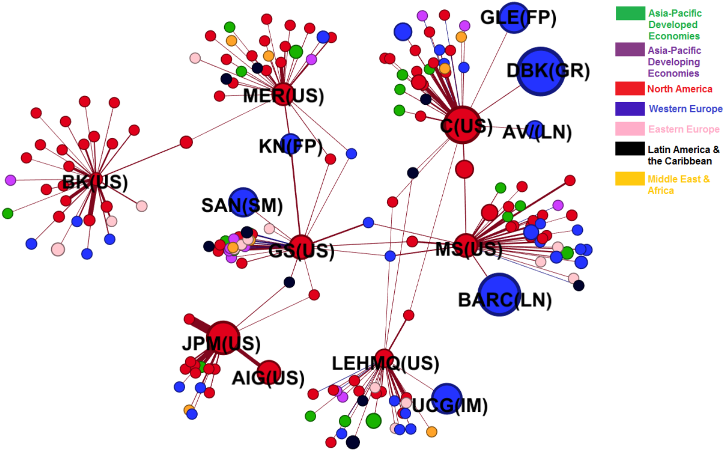



Source: Kenett et al (2010)

# Regularized partial correlation network (1)

- Partial correlation may leave some firms orphan
- There should be no orphans in a fully connected network
- Arguably, financial networks should be fully connected
- Use regularization trick
  - Add penalty to trim procedure
  - Remove edges gradually
  - Stop just before first orphan emerges

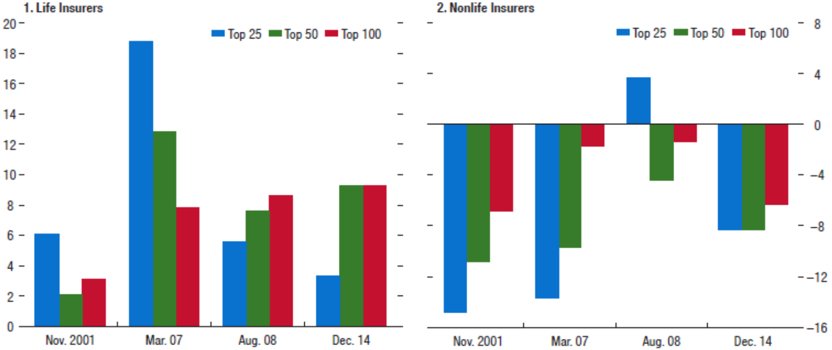
# Regularized partial correlation network (2)




Source: Chan-Lau, Chuang, Duan, and Sun (2017)
Monthly updates for 1928 firms at https://rmicri.org/en/srt/

# Regularized partial correlation network (3)

Figure 3.9. Forward-Looking Default Correlation Networks
*(Percent; over- or underrepresentation of insurers)*




Sources: Risk Management Institute 2015; and IMF staff calculations.
Note: Figure shows over- or underrepresentation of life and nonlife insurers, in the top 25, top 50, and top 100 firms included in the forward-looking default correlation network. For example, a 5 percent value for the top 100 indicates that there are 5 percent more insurance firms among the top 100 than justified by their sample share. Total sample size ranges between 1,263 and 1,679 firms, including 310 to 410 insurers. Owing to the large number of firms, a regularization adjustment was required to generate fully connected networks, where no firm is an orphan (Oh and others 2014).

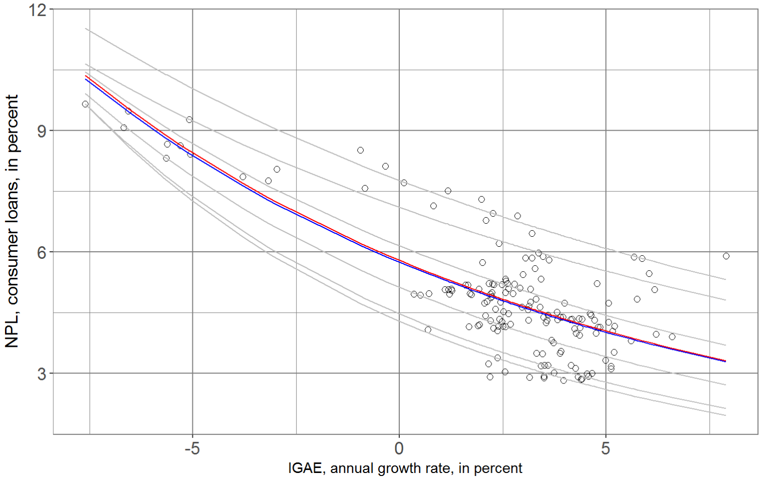
Source: IMF. 2016. Global Financial Stability Report, April

# Quantile regression approaches

# Quantile regression (1)

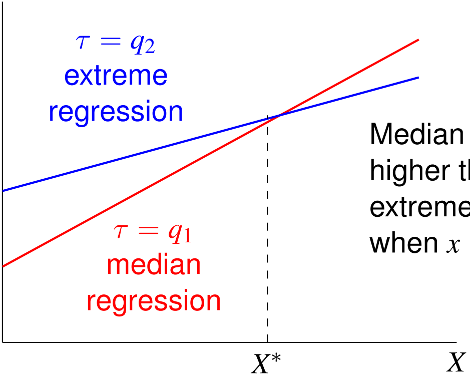
- Richer representation of data beyond mean response
- Whole distribution of responses to covariates
- Semiparametric approach requires no error distribution assumption
- Uses all data points
- Robust to non-normal errors and outliers
- Invariant to transformation

# Quantile Regression (2)



# Quantile Regression (3)

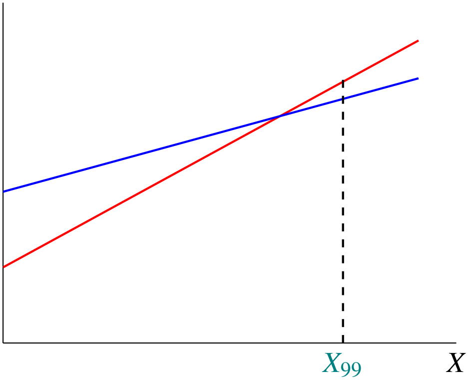
The crossing line problem




Median response higher than extreme response when $x > X^*$ !!!

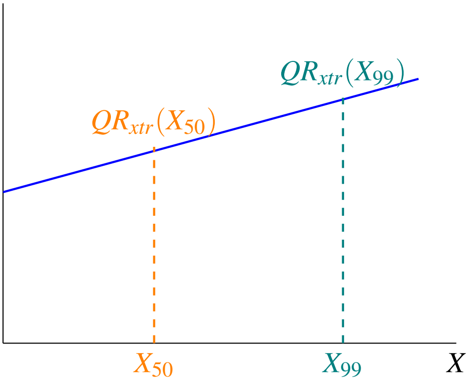
# Quantile Regression (4)

Extreme QR yields "less extreme" outcome than median QR



# Quantile Regression (5)

Good riddance to median QR; introduce $X_{50}$;
systemic risk is $QR_{xtr}(X_{99}) - QR_{xtr}(X_{50})$



# Quantile regression approaches: CoVaR

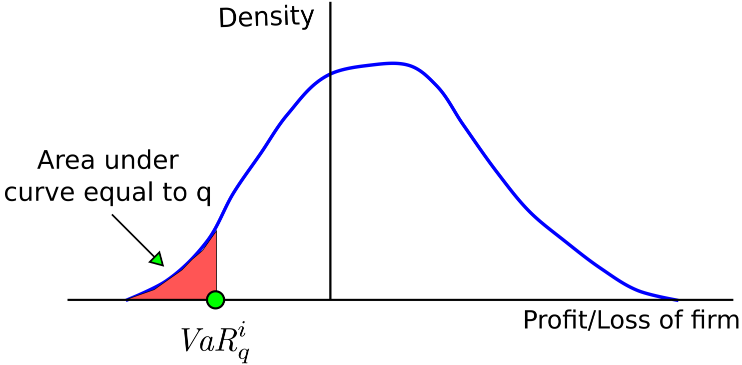
# CoVaR (1)

- Adrian and Brunnermeier (2016)
- $X_i$ risk measure of firm $i$
- Lower $X_i$, higher risk
- Value-at-Risk, $q-th$ quantile

$$\Pr\left(X_i \leq VaR_q^i\right) = q$$

- Unconditional tail risk, $q$ small, i.e. 1%

# CoVaR (2)




Source: Chan-Lau, J.A. 2017. *Quantile regressions and extreme value theory in financial regulation* Lecture Notes, SBS Workshop, Lima, Perú

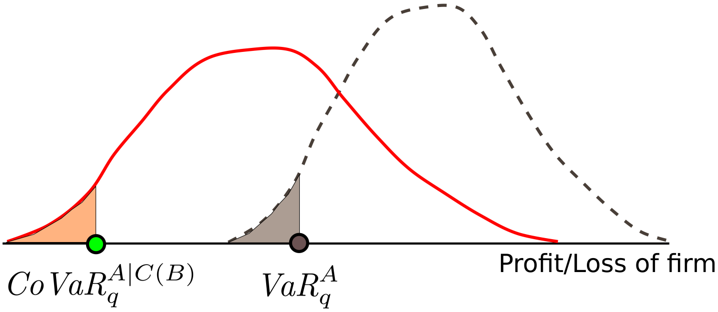
# CoVaR (3)

- Systemic risk focused on contagion
- Contagion = distress of $A$ conditional on distress of $B$
- $C(B)$ event affecting $B$
- $CoVaR_q^{A|C(B)}$ satisfies

$$\Pr\left([X_A|C(B) \leq CoVaR_q^{A|C(B)}]\right) = q$$

# CoVaR (4)

Event $C(B)$ affects location and scale of original P/L distribution




Source: Chan-Lau, J.A. 2017. *Quantile regressions and extreme value theory in financial regulation* Lecture Notes, SBS Workshop, Lima, Perú

# $\Delta CoVaR$ (1)

- Event $C(B)$ can be **normal** or **extreme**
- Normal event

$$\{X_B = VaR^B_{q_{normal}}, q_{\text{extreme}} = 0.5\}$$

- Extreme event

$$\{X_B = VaR^B_{q_{extreme}}, q_{\text{extreme}} = 0.01\}$$

$$\boxed{\Delta CoVaR_q^{A|B} = CoVaR_q^{A|VaR_q^B} - CoVaR_q^{A|VaR_{0.5}^B}}$$

# $\Delta CoVaR$ (2)

- Extreme quantile regression estimation

$$X_A = \alpha(\tau) + \beta(\tau) X_B, \tau = q; \qquad q = q_{\text{extreme}}$$

- $CoVaR$ estimation

$$CoVaR_q^{A|VaR_q^B} = \alpha(\tau = q) + \beta(\tau = q)\, VaR_q^B$$

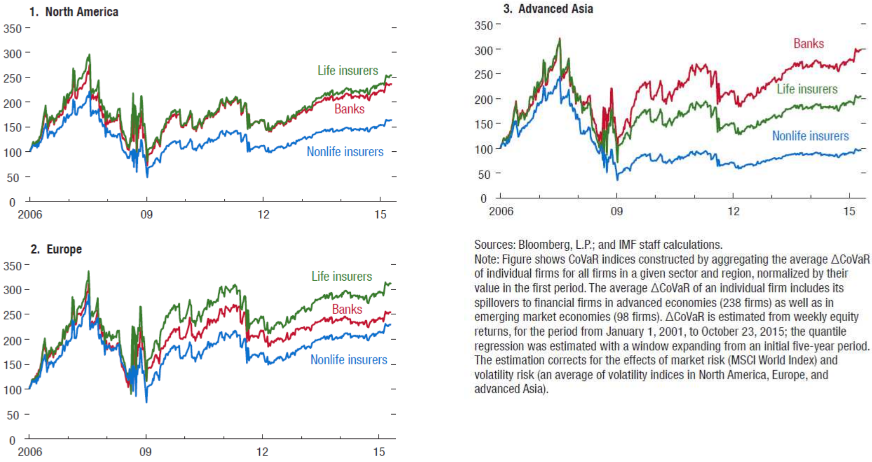
$$CoVaR_q^{A|VaR_{50}^B} = \alpha(\tau = q) + \beta(\tau = q)\, VaR_{0.5}^B$$

- $\Delta CoVaR$ estimation

$$\Delta CoVaR_q^{A|B} = \beta(\tau = q) \times \left(VaR_q^B - VaR_{0.5}^B\right)$$

# $\Delta CoVaR$ (3)

**Figure 3.7. CoVaR Indices**
*(Normalized, 2006 = 100)*




Sources: Bloomberg, L.P.; and IMF staff calculations.
Note: Figure shows CoVaR indices constructed by aggregating the average ΔCoVaR of individual firms for all firms in a given sector and region, normalized by their value in the first period. The average ΔCoVaR of an individual firm includes its spillovers to financial firms in advanced economies (238 firms) as well as in emerging market economies (98 firms). ΔCoVaR is estimated from weekly equity returns, for the period from January 1, 2001, to October 23, 2015; the quantile regression was estimated with a window expanding from an initial five-year period. The estimation corrects for the effects of market risk (MSCI World Index) and volatility risk (an average of volatility indices in North America, Europe, and advanced Asia).

IMF, GFSR April 2016

# Hands-on-Exercise 2: $\Delta CoVaR$

# Adrian and Brunnermeier (2016)

Tutorial page

# Quantile regression approaches: CoRisk

# CoRisk (1)

- Pick any relevant risk measure, i.e. $PD$
- Pick an upper quantile $\tau$, i.e. $\tau = 0.95$
- Quantile regression of $i$ on $j$ and risk factors $X$

$$PD_i = QR(PD_j, X_k; \tau) = \alpha_\tau + \beta_\tau PD_j + \sum_k \beta_{\tau,k} X_k$$

- Find the unconditional $\tau$ and median ($q = 0.50$) quantiles for $PD_i$, $PD_j$

# CoRisk (2)

- CoRisk (in levels)

$$\text{CoRisk} = QR(PD_j(\tau), X_k(q); \tau) - QR(PD_j(q), X_k(q); \tau)$$
$$= \beta_\tau \left(PD_j(\tau) - PD_j(q)\right)$$

- CoRisk (in percent)

$$\text{CoRisk} = \frac{\beta_\tau \left(PD_j(\tau) - PD_j(q)\right)}{PD_i(q)}$$

# Variance decomposition approaches: Diebold-Yilmaz

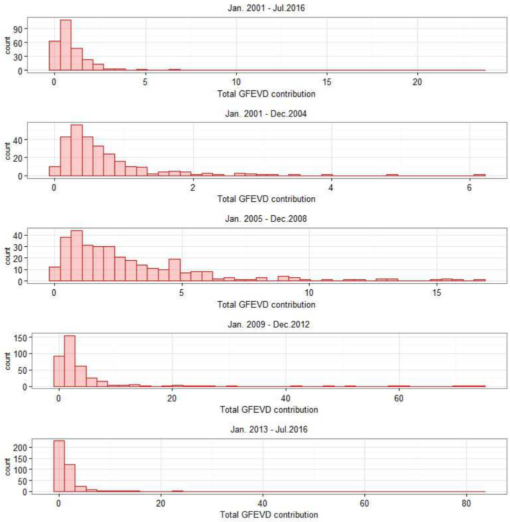
# Diebold-Yilmaz (1): basics

- Start selecting number of firms
- Estimate unrestricted VAR model
  - Equity returns
  - Observable market-based measures
- Network construction
  - Each firm is a node
  - Edges
    - Directional, i.e. from $i$ to $j$
    - Contribution of $i$ to variance decomposition of $j$

# Diebold-Yilmaz (2): variance decomposition

- Generalized Forecast Error Variance Decomposition (GFEVD)
  - Introduced by Pesaran and Shin (1998)
  - VAR ordering does not matter (Koop, Pesaran, and Potter, 1996)
- FEVD from structural VAR adds to unity ...
- ... bug GFEVD does not!
  - Cross-effects of error terms

# Diebold-Yilmaz (3): GFEVDs do not add to one




Source: Chan-Lau (2017)

# Diebold-Yilmaz (4): patching up the GFEVD

- Start with MA representation of VAR

$$Y_t = \sum_{j=0}^{\infty} A_j \epsilon_{t-j}$$

- Pesaran-Shin GFEVD, horizon $h$

$$\theta_{ij}(h) = \frac{\sigma_{ii}^{-1} \sum_{k=0}^{h} (e_j' A_k e_j)^2}{\sum_{k=0}^{h} e_j' A_k \Sigma A_k' e_i}$$

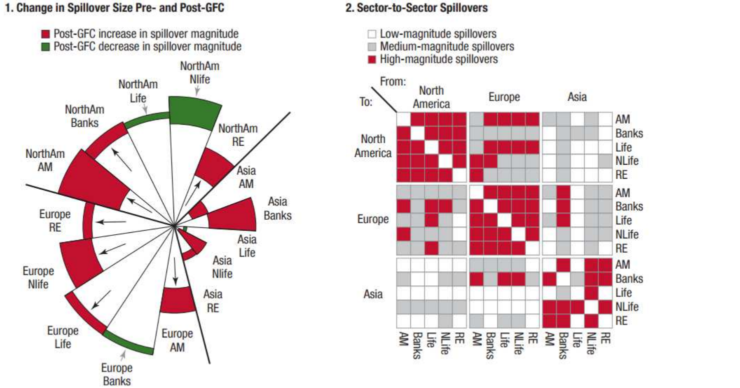
- Diebold-Yilmaz normalization

$$\boxed{\hat{\theta}_{ij}(h) = \frac{\theta_{ij}(h)}{\sum_{k=1}^{n} \theta_{ik}(h)}}$$

- Higher $\sum_{j=1,..,n} \hat{\theta}_{ij}$ implies higher systemic risk ranking

# Diebold-Yilmaz (5): GFSR 2016, Chapter 3

**Figure 3.10. Spillovers between Insurance and Other Financial Sectors**




Sources: Datastream; and IMF staff calculations.
Note: Panel 1 shows change in the size of region and sector spillovers between the pre- and post-GFC periods. Segment length corresponds to region/sector spillover index values. Segment width is used to emphasize differences. Panel 2 shows spillover directionality across regions and sectors. AM = asset management; GFC = global financial crisis; Nlife = nonlife; NorthAm = North America; post-GFC = 2010–15; pre-GFC = 2001–08; RE = reinsurance.

# Diebold-Yilmaz (6): Germany Article IV, 2016

## IMF wrong to label Deutsche world's riskiest bank, says economist

Co-developer of risk methodology used by IMF says it was misapplied when labelling bank riskiest G-Sib

Risk Magazine, online. November 2, 2017

# Diebold-Yilmaz (7): pitfalls in interpreting DY GFEVD

- Economic interpretation of shocks (Koop et al, 1996)
  - Cross-effects of error terms
  - GFEVD less, equal, or greater than one
- Ok for static analysis
  - Risk/vulnerability rankings at any point in time
- Inconsistent for assessing risk evolution over time

*See also Kossner and Wagner (2014) on potential problems with Diebold-Yilmaz spillover indices

# Diebold-Yilmaz (8): simple pitfall example

- Period 1
  - Firm A explains 20 percent of GFEVD of firm B
  - Total GFEVD of firm B equals to 2
- Period 2
  - Firm A explains 50 percent of GFEVD of firm B
  - Total GFEVD of firm B equals to 0.5
- Has Firm A become more systemic to Firm B?
- Ambiguous answer
  - Yes (DY normalization), up 50 percent from 20 percent
  - No, 50 percent of 0.5 is less than 20 percent of 2

# Variance decomposition approaches: Lanne-Nyberg decompositions

# Lanne-Nyberg (1): alternative decomposition

- Diebold-Yilmaz network provide the right intuition but ...
- ... variance decomposition method leads to ambiguous result
- Ambiguity invalidates systemic risk ranking dynamics
- How can we correct it?
- **Use Lanne-Nyberg variance decomposition**

# Lanne-Nyberg (2): Variance Decomposition

- Starts with Generalized Impulse Response Function (GIRF)

$$GI(h, \delta_t, \Omega_{t-1}) = A_h \Sigma e_j \sigma_{jj}^{-1} \delta_j$$

- Lanne-Nyberg GFEVD $\lambda_{ij}(h)$

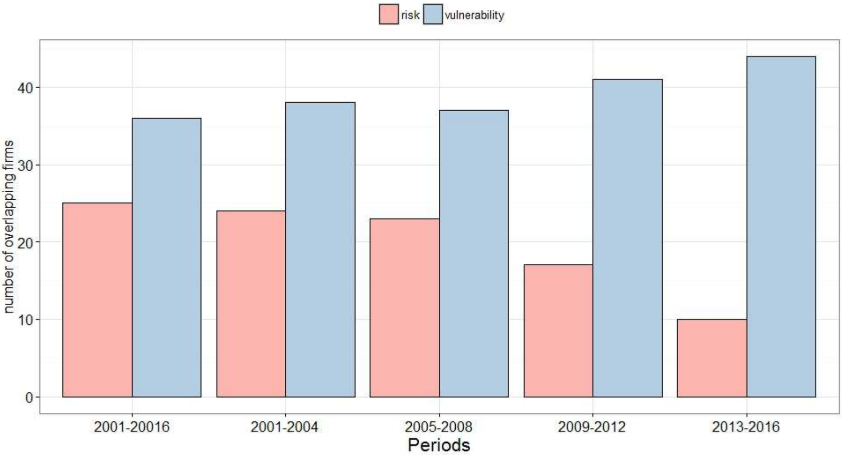
$$\boxed{\lambda_{ij}(h) = \frac{\sum_{k=0}^{h} GI(h, \delta_t, \Omega_{t-1})}{\sum_{j=1}^{n} \sum_{k=0}^{h} GI(h, \delta_t, \Omega_{t-1})}}$$

# Lanne-Nyberg(3): global financial system

- Weekly equity returns
  - 402 firms
  - 34 advanced and emerging market economies
- Sample dates
  - Full sample: 01/01/2001 - 07/31/2016
  - Pre-crisis period: 01/01/2001 - 12/31/2004
  - Lehman Brothers: 01/01/2005 - 12/31/2008
  - Sovereign debt crisis: 01/01/2009 - 12/31/2012
  - Secular stagnation: 01/01/2013 - 07/31/2016
- Lasso Estimation, with 8 lags
- Variance decomposition horizon = 52 weeks
  - Diebold-Yilmaz
  - Lanne-Nyberg

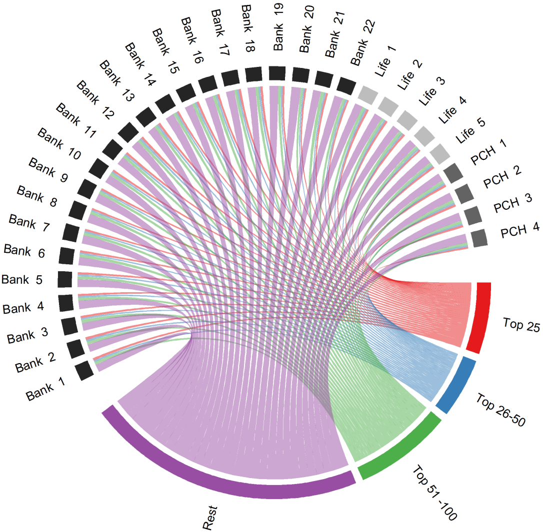
# Lanne-Nyberg (4): comparing systemic rankings

Number of overlapping firms in the top 50 DY and CLNDY rankings




Source: Chan-Lau (2017)

# Lanne-Nyberg (5): FSAP Japan 2016 spillovers



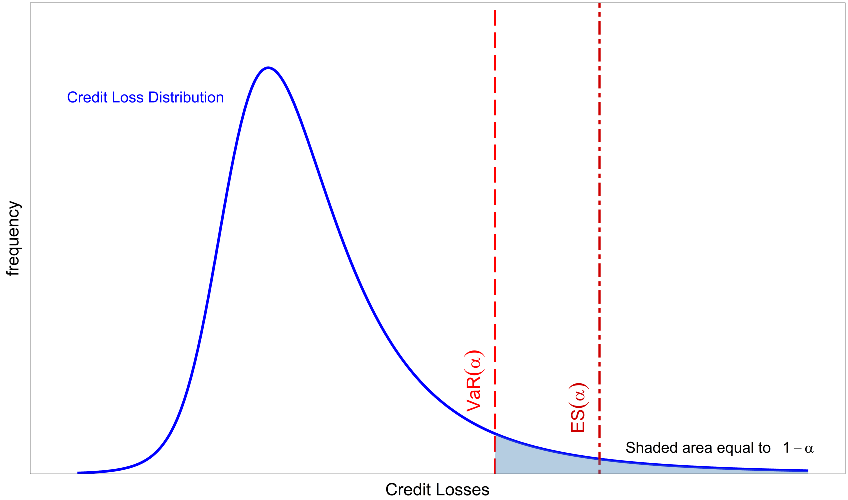
# Outline

# Credit Loss Distribution Analogy

# Credit loss distribution analogy (1)

- Consider a set of firms
- Group the firms in a credit portfolio
- We will use loss distribution to assess a firm's systemic risk
- Focus on tail risk measures
  - Value-at-Risk (VaR)
  - Expected Shortfall (ES)

# Credit loss distribution analogy (2)



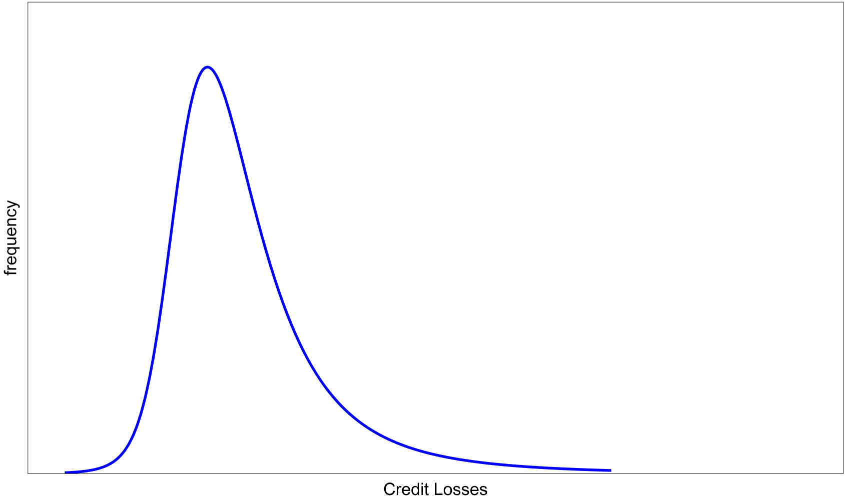
# Credit loss distribution analogy (3)

- Increase default risk of a firm
  - Loss distribution changes
  - Tail risk measures change
- Change in tail measure = systemic risk of firm

# Systemic risk contribution of a firm

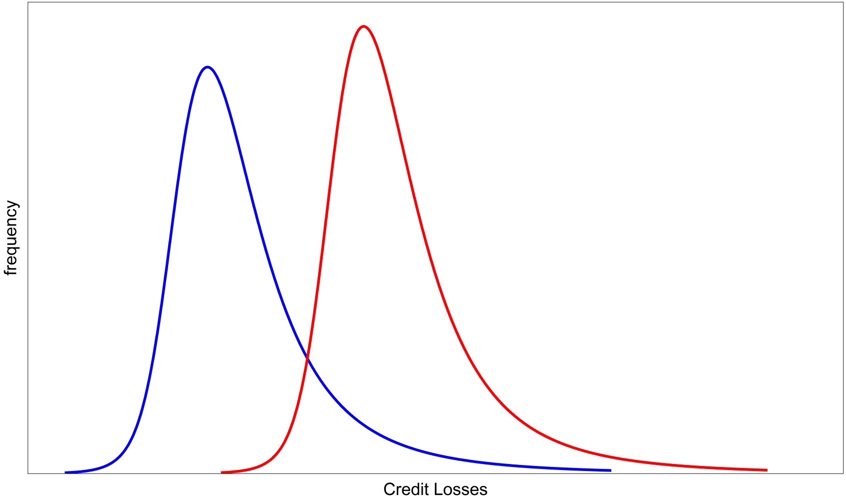
# Systemic risk contribution of a firm (1)

Step 1: Calculate loss distribution, firm under normal conditions



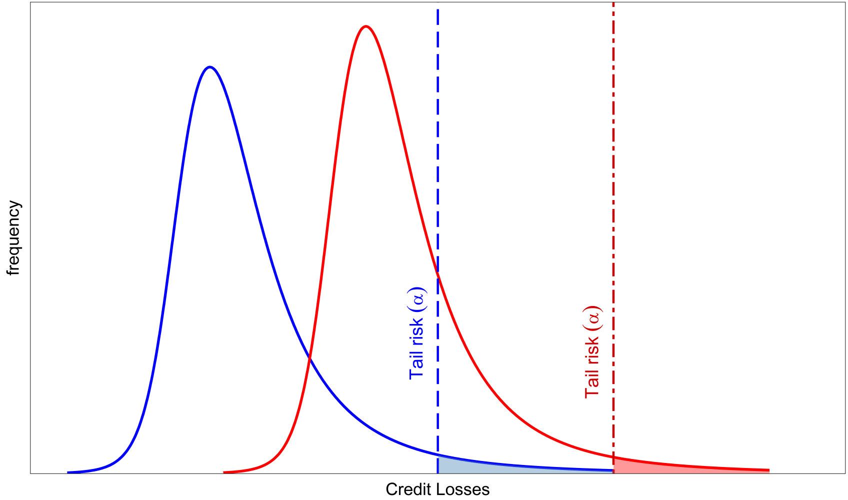
# Systemic risk contribution of a firm (2)

Step 2: Calculate the loss distribution when the firm is stressed



# Systemic risk contribution of a firm (3)

Step 3: Find the tail risk measures of both distributions

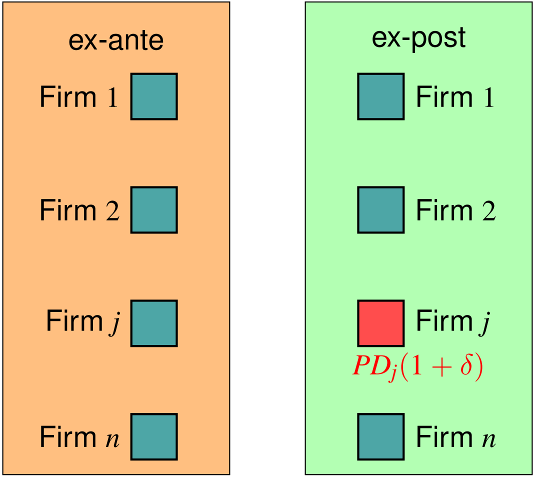


# Systemic risk contribution of a firm (4)

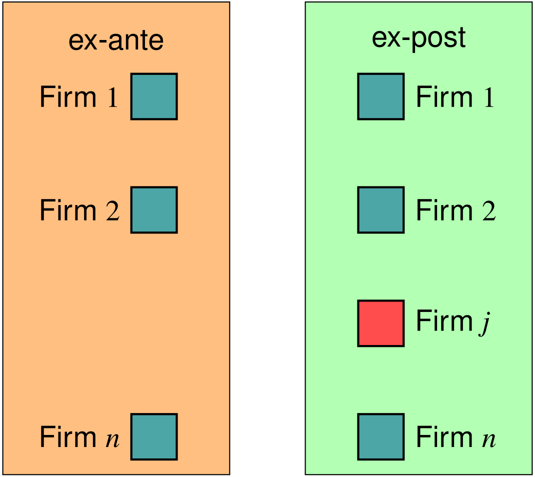
The systemic risk contribution (SRC) is

$$\boxed{SRC(\text{firm}) \equiv \text{Tail Risk}_{\text{ stressed}}(\alpha) - \text{Tail Risk}_{\text{ normal}}(\alpha)}$$

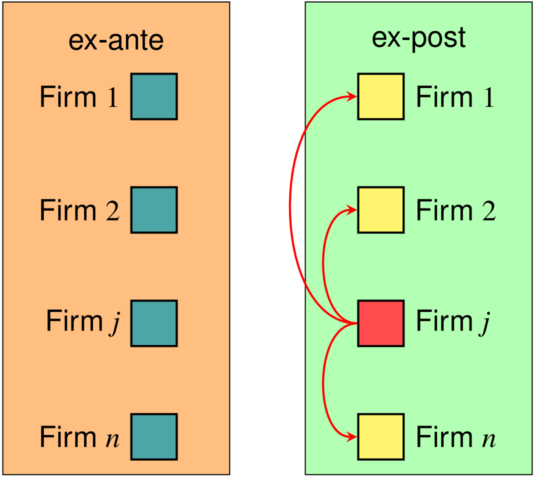
# Huang, Zhang, and Zhu (2011) portfolios



# Tarashev, Borio, and Tsatsaronis (2010) portfolios



# Chan-Lau (2010) portfolios



# Hands-on-Exercise 3:
# Portfolio approaches

- Huang, Zhou, and Zhu (2011)
- Tarashev, Borio, and Tsatsaronis (2010)
- Chan-Lau (2010)

Tutorial page

# Outline

# Indicator-based Measurement Approach (1)

- Global systemic importance
  - (+) Impact of bank failure on global financial system and wider economy
  - (-) Risk of a bank failure
- Subject to Higher Loss Absorbency (HLA) capital
- Indicators approach
  - Looks at negative externalities
  - Reflects multiple dimensions of systemic risk
  - Simple and robust methodology

# Indicator-based Measurement Approach (2)

1. Size
2. Interconnectedness
3. Substitutability
4. Cross-jurisdiction activity
5. Complexity

# Indicator-based Measurement Approach (3)

**Indicator-based measurement approach** — Table 1

| Category (and weighting) | Individual indicator | Indicator weighting |
|---|---|---|
| Cross-jurisdictional activity (20%) | Cross-jurisdictional claims | 10% |
| | Cross-jurisdictional liabilities | 10% |
| Size (20%) | Total exposures as defined for use in the Basel III leverage ratio | 20% |
| Interconnectedness (20%) | Intra-financial system assets | 6.67% |
| | Intra-financial system liabilities | 6.67% |
| | Securities outstanding | 6.67% |
| Substitutability/financial institution infrastructure (20%) | Assets under custody | 6.67% |
| | Payments activity | 6.67% |
| | Underwritten transactions in debt and equity markets | 6.67% |
| Complexity (20%) | Notional amount of over-the-counter (OTC) derivatives | 6.67% |
| | Level 3 assets | 6.67% |
| | Trading and available-for-sale securities | 6.67% |

Source: BCBS (2013)

# Indicator-based Measurement Approach (4)

For each bank

- Score of each indicator

$$\frac{\text{Individual bank amount}}{\text{Aggregate amount across banks}} \times 10000$$

- Category score is simple average over category
- Overall score is simple average over five categories

# Indicator-based Measurement Approach (5)

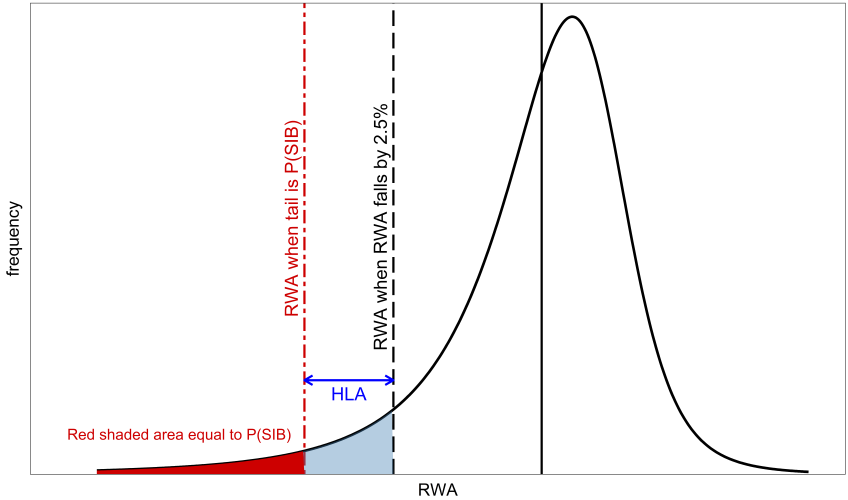
Bucket thresholds, cut-off scores, and HLA requirement

| Bucket | Cut-off scores | HLA requirement (common equity as percent of RWA) |
|---|---|---|
| 5 | 530-629 | 3.5% |
| 4 | 430-529 | 2.5% |
| 3 | 330-429 | 2.0% |
| 2 | 230-329 | 1.5% |
| 1 | 130-229 | 1.0% |

# Calibration of HLA requirement

- Expected Impact Approach
  - Impact of SIB failure greater than a non-SIB reference bank
  - Set $P(SIB) = P(\text{Ref Bank})/\text{Factor}$, where Factor $> 1$
  - Factor = cost of SIB failure relative to reference bank
  - With $P(SIB)$ use empirical distribution or Merton model to determine HLA
- Long run net economic costs of higher capital requirements
- Too-big-to-Fail funding subsidies

# Expected Impact Approach



# FSB 2016 G-SIBs

| Bucket[10] | G-SIBs in alphabetical order within each bucket |
|---|---|
| 5 **(3.5%)** | (Empty) |
| 4 **(2.5%)** | Citigroup<br>JP Morgan Chase |
| 3 **(2.0%)** | Bank of America<br>BNP Paribas<br>Deutsche Bank<br>HSBC |
| 2 **(1.5%)** | Barclays<br>Credit Suisse<br>Goldman Sachs<br>Industrial and Commercial Bank of China Limited<br>Mitsubishi UFJ FG<br>Wells Fargo |
| 1 **(1.0%)** | Agricultural Bank of China<br>Bank of China<br>Bank of New York Mellon<br>China Construction Bank<br>Groupe BPCE<br>Groupe Crédit Agricole<br>ING Bank<br>Mizuho FG<br>Morgan Stanley<br>Nordea<br>Royal Bank of Scotland<br>Santander<br>Société Générale<br>Standard Chartered<br>State Street<br>Sumitomo Mitsui FG<br>UBS<br>Unicredit Group |

Source: FSB (2016)

# Proposed Revisions to Methodology (1)

Overview of proposed revisions to the G-SIB assessment framework — Table 1

| Category | Indicator | Indicator weight: Current framework | Indicator weight: Revised framework |
|---|---|---|---|
| Cross-jurisdictional activity (20%)† | Cross-jurisdictional claims | 1/10 = 10% | 1/10 = 10% |
| | Cross-jurisdictional liabilities | 1/10 = 10% | 1/10 = 10% |
| Size (20%)†† | Total exposures | 1/5 = 20% | 1/5 = 20% |
| Interconnectedness (20%)†† | Intra-financial system assets | 1/15 = 6.67% | 1/15 = 6.67% |
| | Intra-financial system liabilities | 1/15 = 6.67% | 1/15 = 6.67% |
| | Securities outstanding | 1/15 = 6.67% | 1/15 = 6.67% |
| Substitutability/financial institution infrastructure (20%)* | Assets under custody | 1/15 = 6.67% | 1/15 = 6.67% |
| | Payment activity | 1/15 = 6.67% | 1/15 = 6.67% |
| | Underwritten transactions in debt and equity markets | 1/15 = 6.67% | 1/30 = 3.33% |
| | Trading volume | | 1/30 = 3.33% |
| Complexity (20%)†† | Notional amount of OTC derivatives | 1/15 = 6.67% | 1/15 = 6.67% |
| | Level 3 assets | 1/15 = 6.67% | 1/15 = 6.67% |
| | Trading and available-for-sale securities | 1/15 = 6.67% | 1/15 = 6.67% |

* no cap on the substitutability category

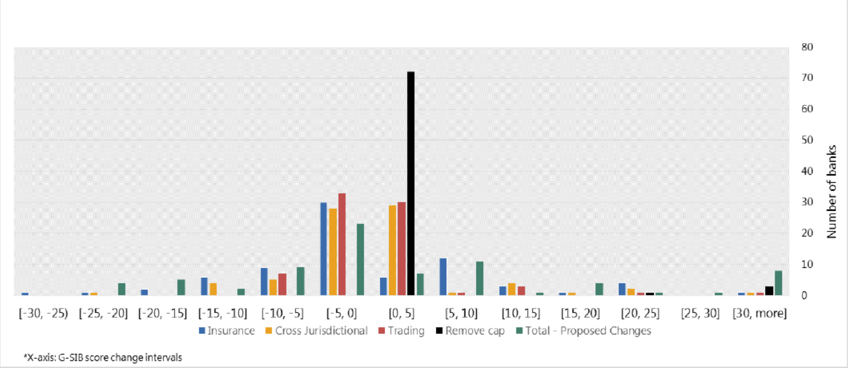
† amended to include derivatives in claim and liabilities definitions, on a consolidated basis.

†† expanded scope of consolidation to include exposures under insurance subsidiaries

Source: BCBS (2017)

# Proposed Revisions to Methodology (2)

Histogram of the impact on G-SIB scores for each of the proposed changes Graph 1




Source: BCBS (2017)

# Outline

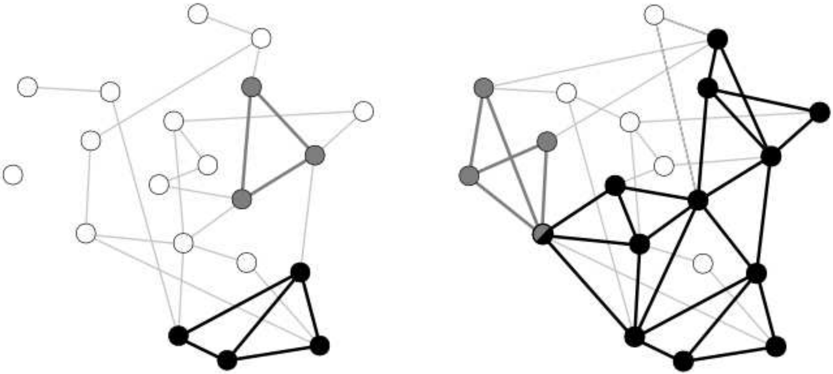
# Systemic communities (1)

- Cross-section systemic risk
  - Too-connected-to-fail (TCTF)
  - Too-important-to-fail (TITF)
- TCTF captured with centrality measures
- Communities capture TITF
  - Group of (fully or not) connected firms
  - Failure of one firm affects community
- Centrality and community analysis are complementary

# Systemic communities (2)

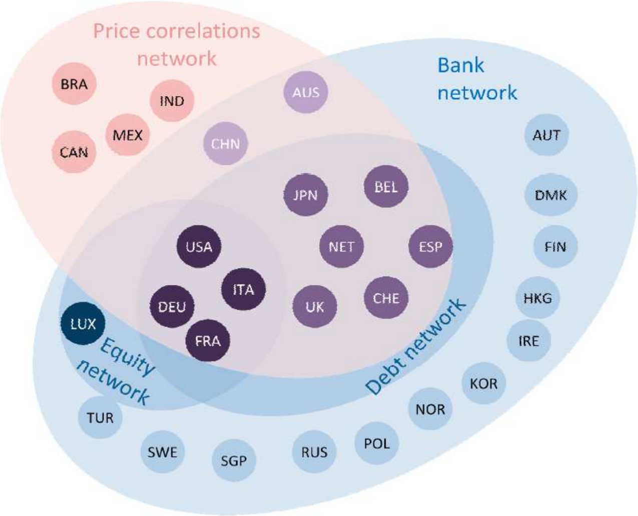
- Community detection
  - Active area of research
  - Physics
  - Biology
  - Computer science
  - Computational Social Sciences
- Methods applied in finance/economics
  - Clique percolation
  - Edge betweeness
  - Infomap

# Systemic communities (3): clique percolation method



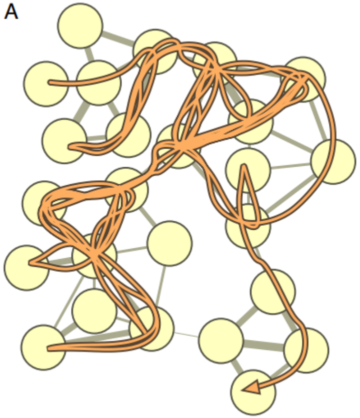
Source: Derenyi, Palla, and Vicsek (2005)

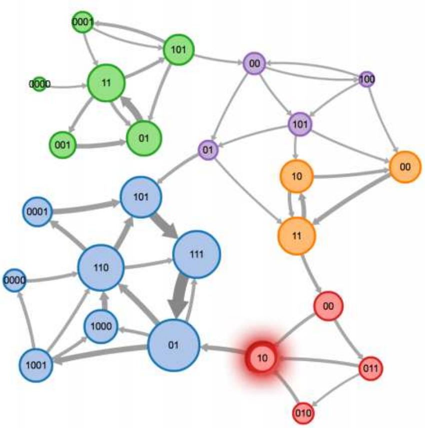
# Systemic communities (4): IMF Mandatory FSSA 2013




Source: Demekas et al (2013)

# Systemic communities (5): Infomap algorithm

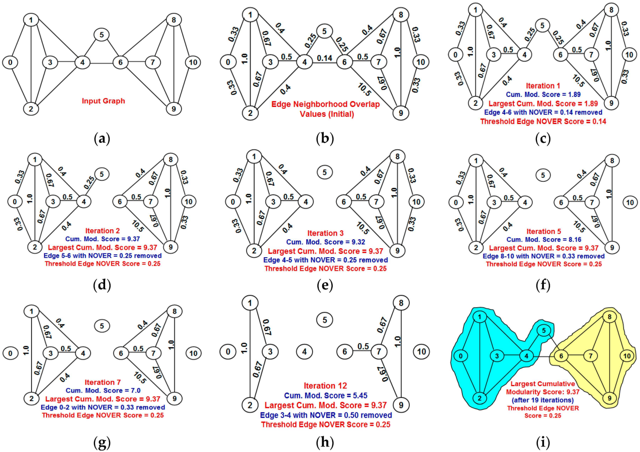



Encoded random walker

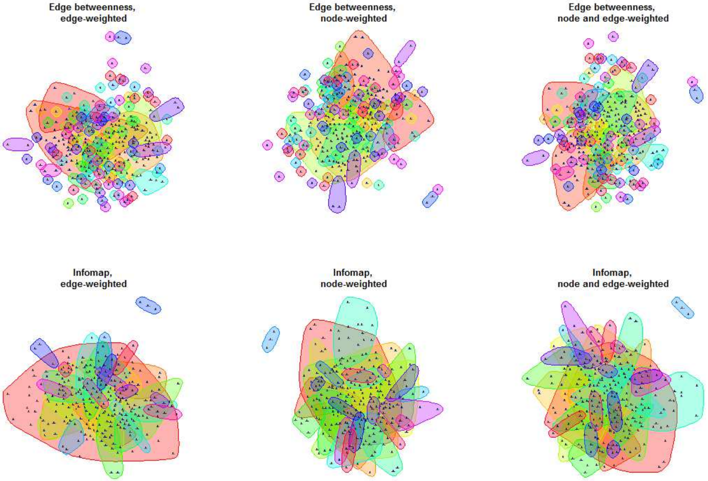
Source: Rosvall and Bergstrom (2008); Bohlin et al (2014)

# Systemic communities (6): edge betweenness



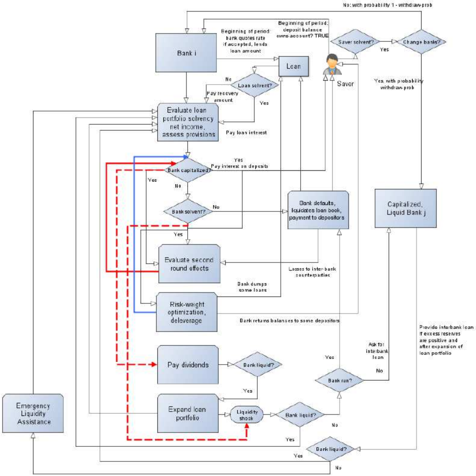

Source: Meghanathan, N. 2016. A greedy algorithm for neighborhood overlap-based community detection. *Algorithms* 9.

# Systemic communities (7): global financial network



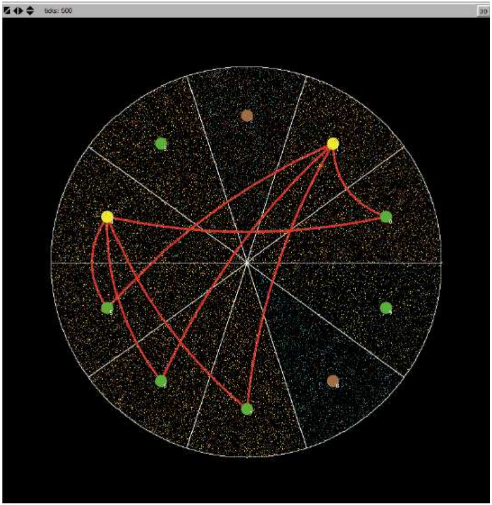

Source: Chan-Lau (2017)

# Agent-based networks (1)



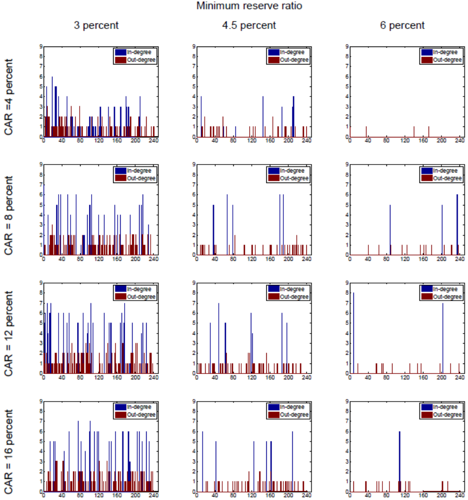

Source: Chan-Lau (2017)

# Agent-based networks (2)




Source: Chan-Lau (2017)

# Agent-based networks (3)




Source: Chan-Lau (2017)

# Outline

# Summary

- Financial systems are networks
- Networks construction
  - Direct exposures
  - Market-based measures
- Analytical methods
  - Rapid development going on
  - Useful and easy to implement
    - Balance-sheet network analysis
    - CoVaR (and CoRisk)
    - Portfolio approaches
- New approaches finding their way into policy
- Self-study: keep up with analytics to remain relevant!

# Thank You

# References (1)


## Conceptual Overview

- Bookstaber, R., Kenett,D. 2016 Looking deeper, seeing more: a multilayer map of the financial system. OFR Brief Series 16-06.
- Borio, C. 2001. Towards a macroprudential framework for financial supervision and regulation. BIS WP No. 128.
- Brunnermeier, M., Pedersen, L. 2009. Market liquidity and funding liquidity. *Review of Financial Studies* 22.
- Zhao, Z., Zhang, W., Shi, S. 2013. Common asset holdings and systemic risk of financial network. *Procedia Computer Science* 17.

## Direct Exposure Methods

- Bardoscia, M., Battiston, S., Caccioli, F., Caldarelli, G. 2015. DebtRank: a microscopic foundation for shock propagation. PLOS One. June 19.
- Bargigli, L., di Iasio, G., Infante, L., Pierobon, F. 2015. The multiplex structure of interbank networks. *Quantitative Finance*.
- Chan-Lau, J.A. 2010. Network analysis model. User's guide. Internal document. Banco Central de Chile.
- Espinosa, M., Sole, J. 2010. Cross-border financial surveillance: a network perspective. IMF WP 10/105.
- Eisenberg, L., Noe, T.H. 2001. Systemic risk in financial systems. *Management Science* 47.
- Furfine, C. 2003. Interbank exposures: quantifying the risk of contagion. *J. of Money, Credit and Banking* 35.
- Jo, J.-H. 2012. Managing systemic risk from the perspective of the financial network under macroeconomic distress. FSI Award 2012 Winning Paper. Financial Stability Institute, Basel.
- Sun, A., Chan-Lau, J.A. 2017. Financial networks and interconnectedness in an advanced emerging market economy. *Quantitative Finance*, in print.
- Upper, C. 2011. Simulation methods to assess the danger of contagion in interbank markets. *J. of Financial Stability* 7.

# References (2)

## Market-based Methods


- Adrian, T., Brunnermeier, M. 2016. CoVaR. *American Economic Review* 106.
- Barigozzi, M., Brownless, C.T. 2016. NETS: Network estimation for time series. Mimeo, LSE and U. Pompeu Fabra.
- Billio, M. Getmansky, M., Lo, A., Pellizon, L. 2012. Econometric measures of connectedness and systemic risk in the finance and insurance sectors. *J. of Financial Economics* 104.
- Chan-Lau, J.A. 2009. Default risk codependence in the global financial system: was the Bear Stearns bailout justified? In Gregoriu, G. *The Banking Crisis Handbook*. John Wiley and Sons
- Chan-Lau, J.A. 2017. Variance decomposition networks: potential pitfalls and a simple solution. IMF WP 17/107.
- Chan-Lau, J.A., Chuang, C., Duan, J.-C., Sun, W. 2017. Financial network and systemic risk via forward-looking partial default correlations. Mimeo. National University of Singapore.
- Craig, B., Saldias, M., 2016. Spatial dependence and data-driven networks of international banks. IMF WP 16/184.
- Diebold, F., Yilmaz, M. 2014. On the network topology of variance decompositions: measuring the connectedness of financial firms. *J. of Econometrics* 182.
- Kenett, D., Tumminello, M., Madi, A., Gur-Gershgoren, G., Mantegna, R., Ben-Jacob, E. 2010. Dominating clasp of the financial sector revealed by partial correlation analysis of the stock market. PLOS One December 20.
- Klossner, S., Wagner, S. 2014. Exploring all VAR orderings for calculating spillovers? Yes, we can! A note on Diebold and Yilmaz. *J. of Applied Econometrics* 29.

# References (3)


## The Portfolio Approach

- Tarashev, N., Borio, C., Tsatsaronis, K. 2010. Attributing systemic risk to individual institutions. BIS WPs No. 308.
- Chan-Lau, J.A. 2010. Regulatory Capital Charges for Too-Connected-to-Fail Institutions: A Practical Proposal. *Financial markets, Institutions, and Instruments* 19 (Lead Article).
- Chan-Lau, J.A. 2013. *Systemic Risk Assessment and Oversight*. Risk Books. London.
- Huang, X., Zhou, H., Zhu, H. 2011. Systemic risk contributions. FEDS WP 2011-08. Board of Governors of the Federal Reserve.

## Systemic communities

- Bohlin, L., Edler, D., Lancichinetti, A., Rosvall, M. 2014. Community detection and visualization of networks with the map equation framework. Mimeo.
- Chan-Lau, J.A. 2017. Systemic centrality and systemic communities in financial networks. Mimeo, IMF.
- Demekas, D., Chan-Lau, J.A., Rendak, N.,Ohnsorge, F., Youssef, K., Caceres, C., Tintchev, K. 2013. Mandatory financial stability assessments under the financial sector assessment program: update. IMF.
- Derenyi, I., Palla, G., Vicsek, T. 2005. Clique percolation in random networks. *Physics Review Letters* 94.
- Girvan, M., Newman, M.E.J. 2002. Community structure in social and biological networks. *Proc. of the National Academy of Sciences* 99.
- Palla, G., Farkas, I.J., Vicsek, T. 2005. Uncovering the overlapping community structure of complex networks in nature and society. *Nature* 435.
- Rosvall, M., Bertstrom, C. 2008. Maps of random walks on complex networks reveal community structure. *Proc. of the National Academy of Sciences* 105.

# References (4)


### Agent-based models

- Chan-Lau, J.A. 2014. Regulatory requirements and their implications for bank solvency. Mimeo. IMF and NUS.
- Chan-Lau, J.A. 2017. ABBA: an Agent-based model of the banking system. IMF WP/17/136.
- Halaj, G., Kok C.. 2014. Modeling emergence of the interbank networks. ECB WP No. 1646.
- Liu, A., Paddrik, M., Yang, S., Zhang, X. 2016. Interbank contagion: an agent-based model approach to endogenously formed networks. OFR WP 16-15.
- Turrell, A. 2016. Agent-based models: understanding the economy from the bottom up. Quarterly bulletin Q4. Bank of England.

### Global systemic institutions

- BCBS. 2012. A framework for dealing with domestic systemically important banks. Basel.
- BCBS. 2017. Global systemically important banks - revised assessment framework. Consultative document. Basel.
- FSB. 2016. 2016 list of global systemicallly important banks (G-SIBs).
- IAIS. 2016. Global systemically important insurers: updated assessment methodology.

### Other useful references

- Bisias, D., Flood, M., Lo, A.W., S. Valavanis. 2012. A survey of systemic risk analytics. OFR WP 0001.
- Gai, P. 2016. *Systemic Risk: the dynamics of modern financial systems.* Oxford University Press.
- Glasserman, P., Young, H.P. 2016. Contagion in financial networks. *J. of Economic Literature* 54.
- Hamill, L., Gilbert, N. 2016. *Agent-based modelling in economics*. John Wiley and Sons.