Contagion and Systemic Risk

Paul Glasserman
Columbia University

31st International Congress of Actuaries
Berlin
June 4-8, 2018

Are Insurance Companies A Source of Systemic Risk?

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- Financial Stability Board definition:

  Systemically important financial institutions are financial institutions whose distress or disorderly failure, because of their size, complexity and systemic interconnectedness, would cause significant disruption to the wider financial system and economic activity.

Are Insurance Companies A Source of Systemic Risk And If So, How?

- In the U.S., AIG and Hartford received TARP funds; Allstate, Genworth, Prudential applied
- Large losses through the crisis from
  - Variable annuity guarantees
  - Securities lending

- As large asset owners, may contribute to fire sales

- Opaque use of derivatives – hedging risks or enhancing performance?

- Large providers of critical functions

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- Insurance liabilities are not “runnable”
- Separate accounts overstate assets
- Accounting treatment of margins in reserve understate capital
- Insurers are receivers of systemic risk, not sources

Contagion: How Do Shocks Spread Through The Financial System?

- Direct defaults
  - AIG was bailed out over fears that it would fail to make payments to ~30 banks, which could fail
- Withdrawal of funding liquidity
  - Following the Lehman failure, short-term funding froze, (nearly) bringing down other banks
- Price contagion through common holdings and fire sales
  - June 2007 sell-off of subprime MBS accelerates general decline in subprime MBS
- Correlated assets and liabilities
  - Insurers exposed to common weather risks and market performance
- Information cascades
  - Bad news at one firm leads investors, customers to make inferences at other firms

Correlation: NYU Stern SRISK Measure – May 23, 2018

SRISK = expected capital shortfall conditional on a market decline of more than 10%

Capital shortfall = k(Debt + Equity) – Equity

k = prudential capital ratio (e.g., 8%)

Debt in book value, Equity in market value

Firm's beta to the market has a big effect – in this sense, correlation driven

US Financials Systemic Risk Top Ten

TOP 10	SRISK	LRMES	LVG
Citigroup Inc	40,842	41.08	10.64
Goldman Sachs Group Inc/The	28,997	48.82	10.93
Prudential Financial Inc	27,462	48.93	14.81
Morgan Stanley	21,411	53.42	9.16
MetLife Inc	18,192	44.35	12.08
Lincoln National Corp	9,617	49.07	14.83
Voya Financial Inc	8,438	43.43	19.20
Ally Financial Inc	6,503	43.22	14.55
Genworth Financial Inc	5,979	47.83	51.70
Principal Financial Group Inc	3,428	46.76	9.67

SRISK: Banks Versus Insurers (Coleman et al. 2017, GRI)

- Remove segregated accounts from Debt
- What is the right capital ratio for insurers? (5.5% in Europe, 7.5% in Canada)
- SRISK not reflective of 2008 losses

Table 2. SRISK and SRISK[a] for US and Canadian insurance companies (June 30, 2016)[9]

US insurance companies (in million USD)

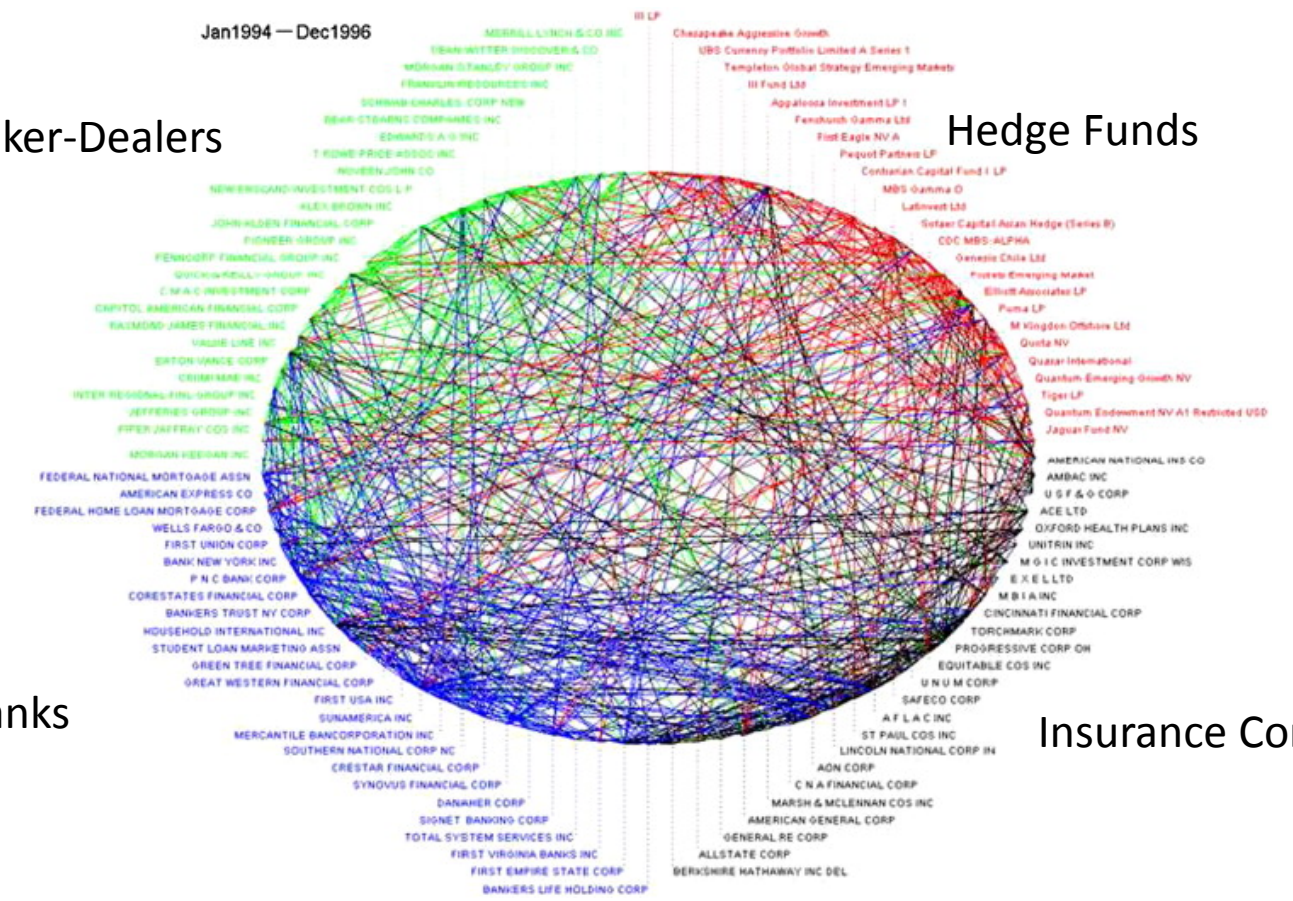
	SRISK	SRISK[a]	Seg.Fund	Debt
Prudential	43,835	21,315	281,501	723,730
Metlife	54,754	30,270	306,047	841,463
Lincoln National	16,928	7,048	123,506	241,060
Hartford	7,943	0	118,361	209,381
Genworth	6,725	6,115	7,624	91,200

Canadian insurance companies (in million CAD)

	SRISK	SRISK[a]	Seg.Fund	Debt
Manulife	34,739	12,337	298,684	656,000
Great-West Life	7,303	0	193,001	365,714
Sun Life	3,079	0	89,795	225,721
Intact	0	0	0	15,362

Billio et al. (2012) Econometric Measure of Interconnectedness

Financial system increasingly interconnected over time

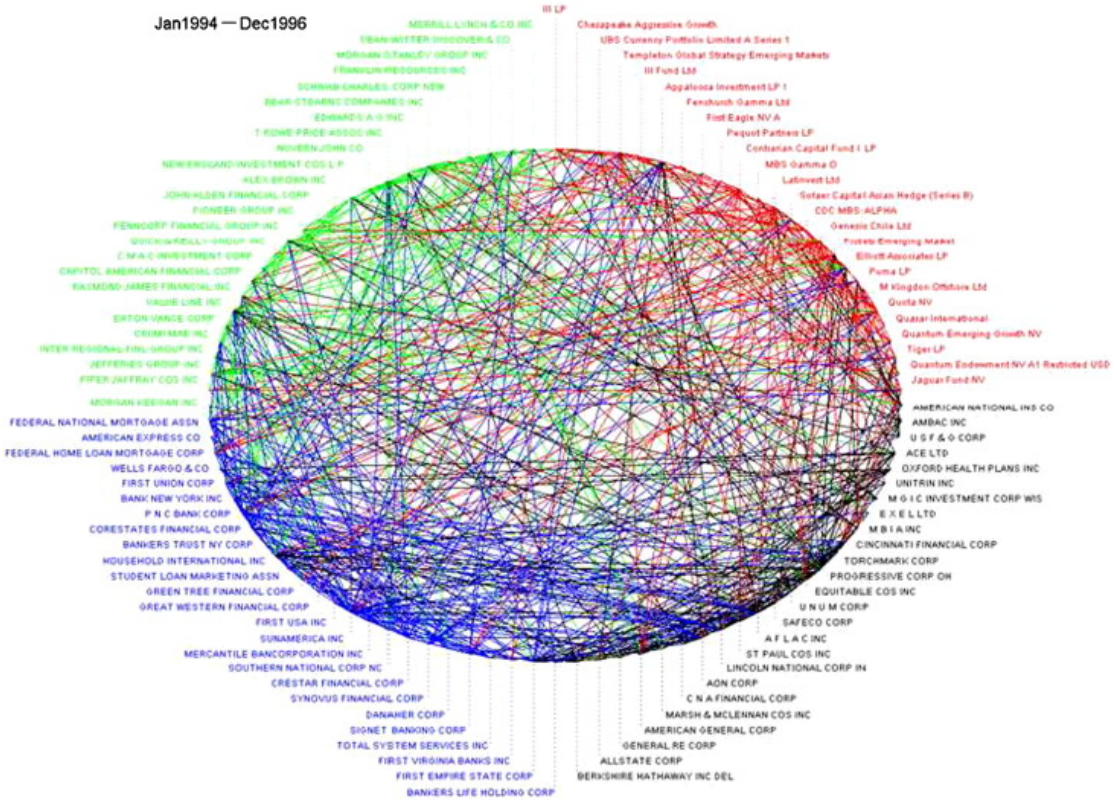


$$R^i_{t+1} = a^i R^i_t + b^{ij} R^j_t + e^i_{t+1},$$

$$R^j_{t+1} = a^j R^j_t + b^{ji} R^i_t + e^j_{t+1},$$

Granger causality network: link from company i to company i if b^{ji} is nonzero

Granger Causality Network Using Market Returns R^i_t



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Granger causality network: link from company i to company i if b^{ji} is nonzero

Pros

- Uses abundant, frequent market data
- Based on forward-looking market view

Cons

- How do we interpret a causal relation from one return to another?
- Does this capture how shocks spread?

IMF Report Systemic Risk Rankings (Chan-Lau 2017)

Table 3c. Systemic risk rankings, all firms: January 2009 – December 2012
(ranking based on a VAR(8) specification)

	Systemic risk ranking			
Ranking	Diebold-Yilmaz network		Corrected Lanne-Nyberg-Diebold-Yilmaz network	
1	RADIAN GROUP INC	UNITED STATES	AEGON N.V.	NETHERLANDS
2	KBC GROUP NV	BELGIUM	ING GROEP N.V.	NETHERLANDS
3	BANK OF IRELAND	IRELAND	ALLIANZ SE	GERMANY
4	ALLIED IRISH BANKS PLC	IRELAND	AFLAC INC	UNITED STATES
5	MGIC INVESTMENT CORP/ WI	UNITED STATES	LOEWS CORP	UNITED STATES
6	ING GROEP N.V.	NETHERLANDS	SAMPO OYJ	FINLAND
7	SOCIETE GENERALE	FRANCE	METLIFE INC	UNITED STATES
8	PHOENIX COMPANIES INC	UNITED STATES	UNUM GROUP	UNITED STATES
9	BARCLAYS PLC	UNITED KINGDOM	AXA SA	FRANCE
10	CREDIT AGRICOLE SA	FRANCE	AVIVA PLC	UNITED KINGDOM

Diebold-Yilmaz Network Measure

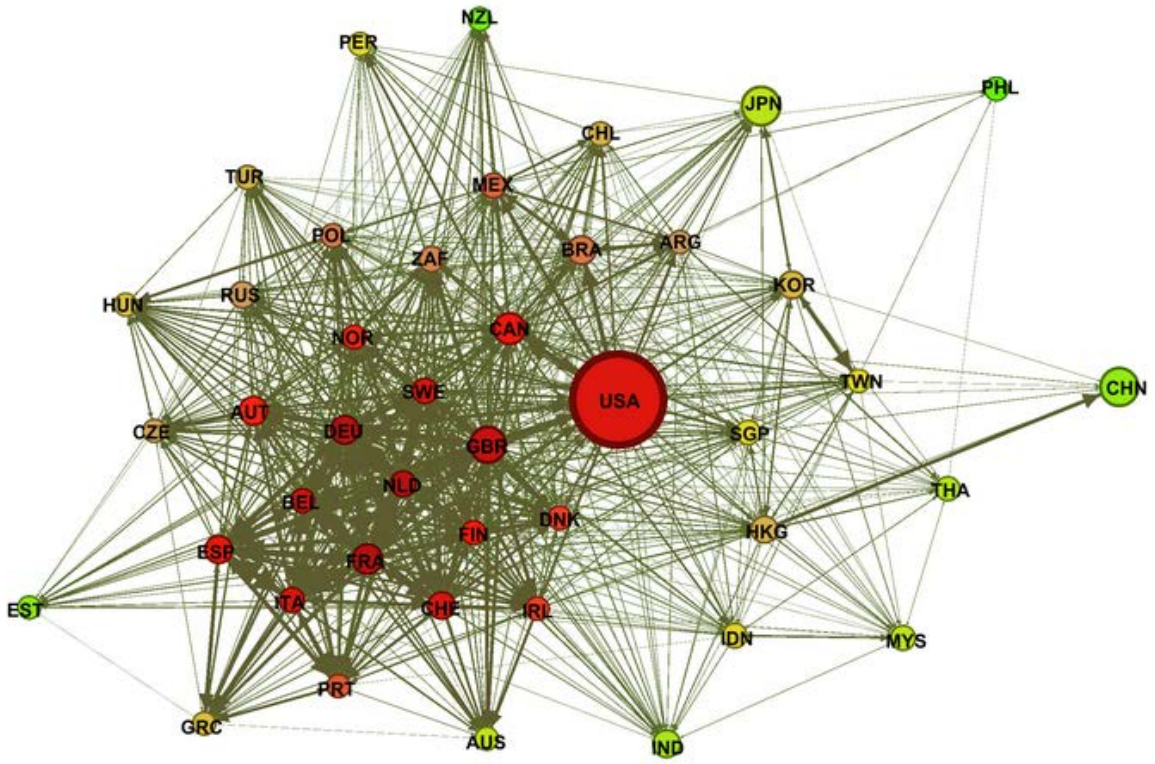
- Considers interconnections between firm *volatilities* rather than returns
- Variance decomposition measure: How much of company A's future volatility is explained by company B's current volatility
  - This gives the strength of the connection from B to A

- Systemic risk ranking ranks firms by strength of *outgoing* connections
  - Influence on others

- Vulnerability ranking ranks firms by strength of *incoming* connections
  - Influence from others

- Similar pros and cons to Granger causality networks, with advantages of using volatilities rather than returns

Diebold-Yilmaz Interconnectedness: Network and Index Over Time



Index of Volatility Connectedness

Network Models of Direct Defaults: Interlinked Balance Sheets

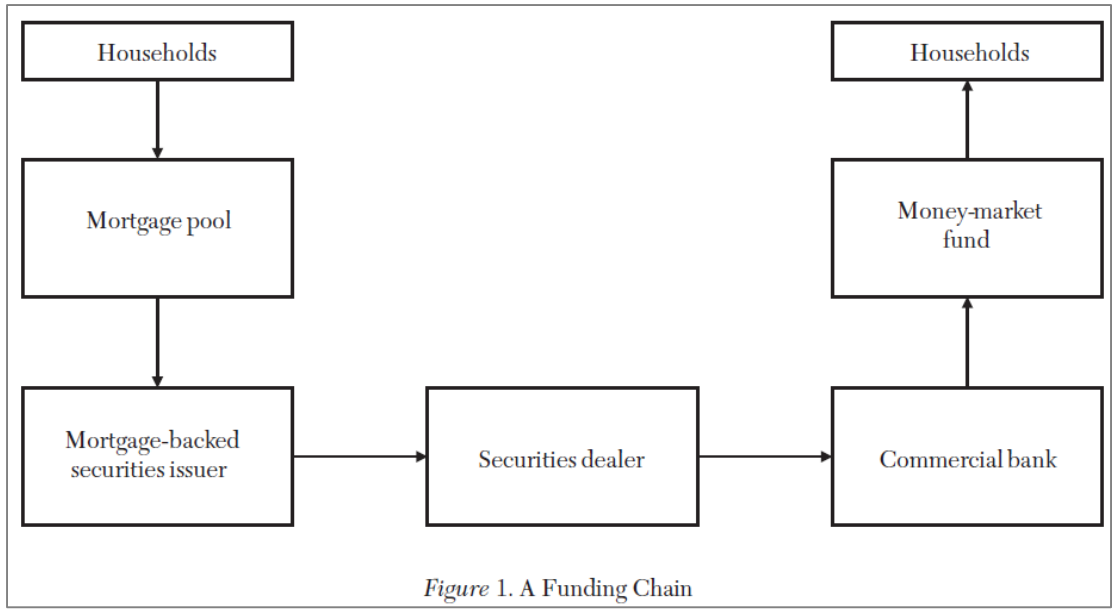


Figure 1. A Funding Chain

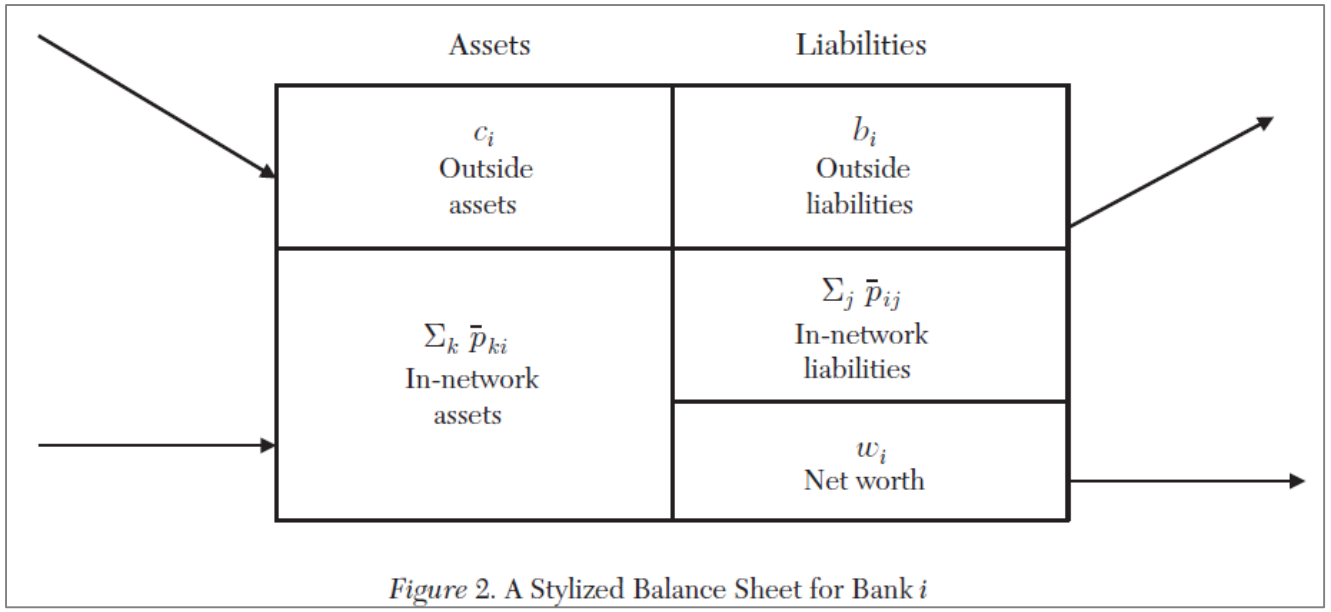


Figure 2. A Stylized Balance Sheet for Bank *i*

A Network of Payment Obligations

Arrows show payment obligations

Values in boxes indicate net worth

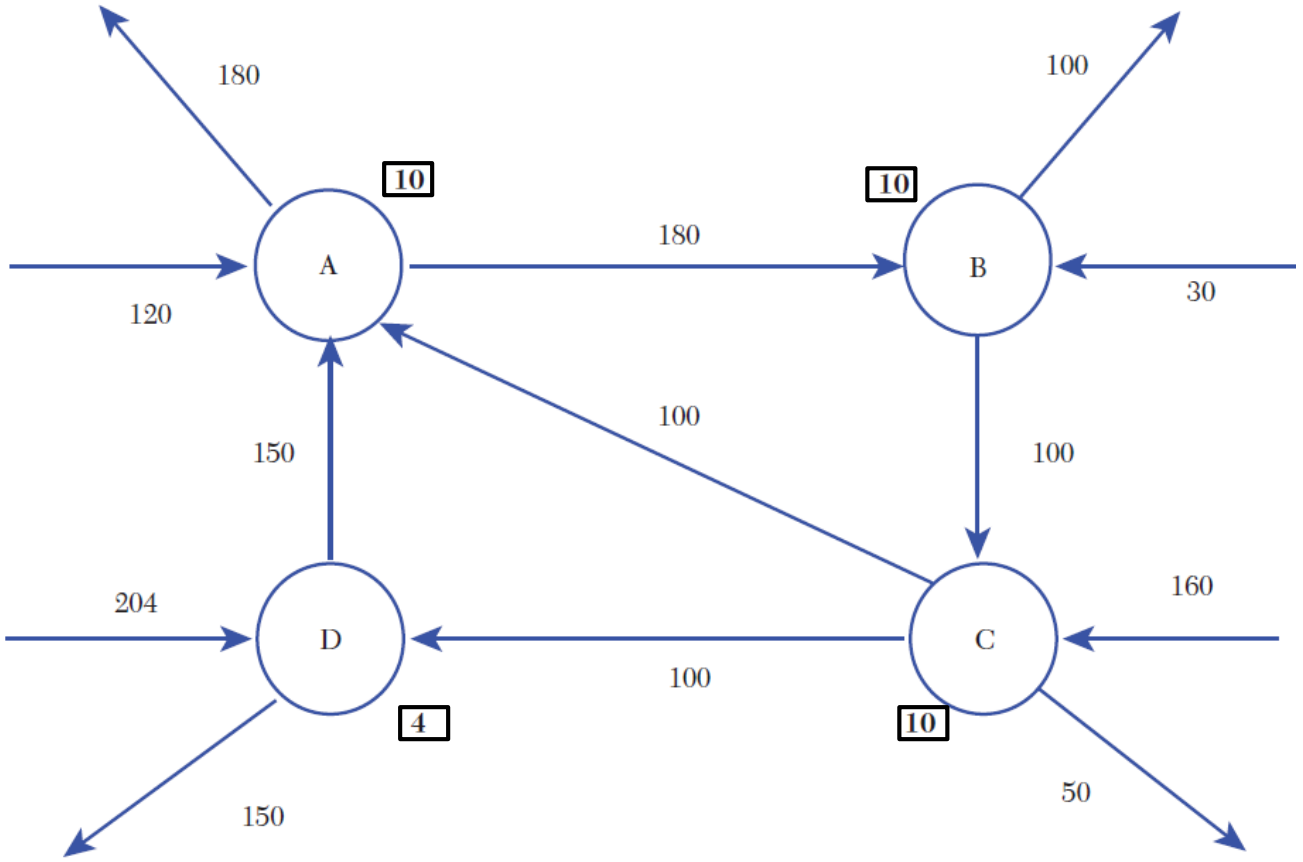
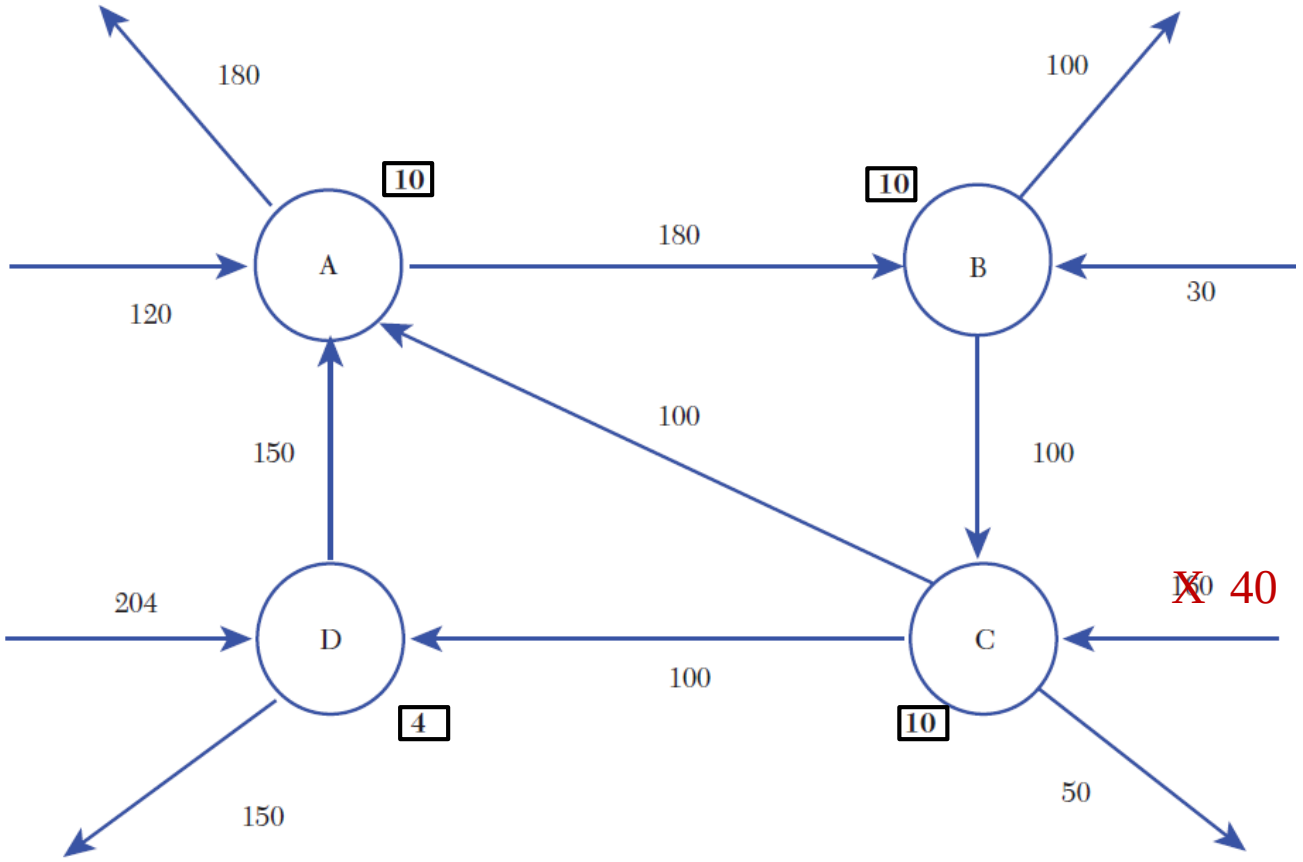


Figure 3. A Hypothetical Financial Network Showing Payments Due

Initial Shock to Network



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Initial shock reduces payment of 160 to 40.

What is the impact on the network?

The Shock Spreads

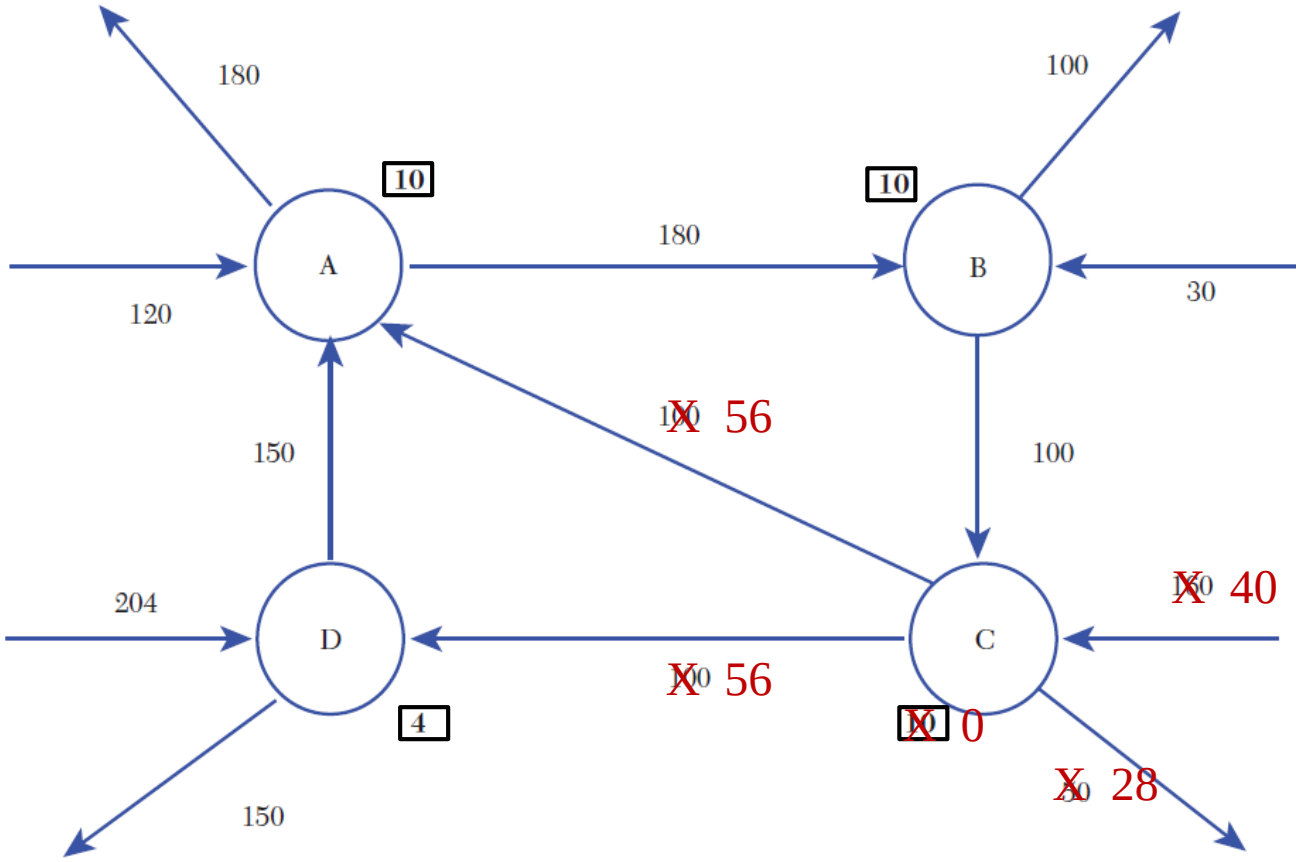


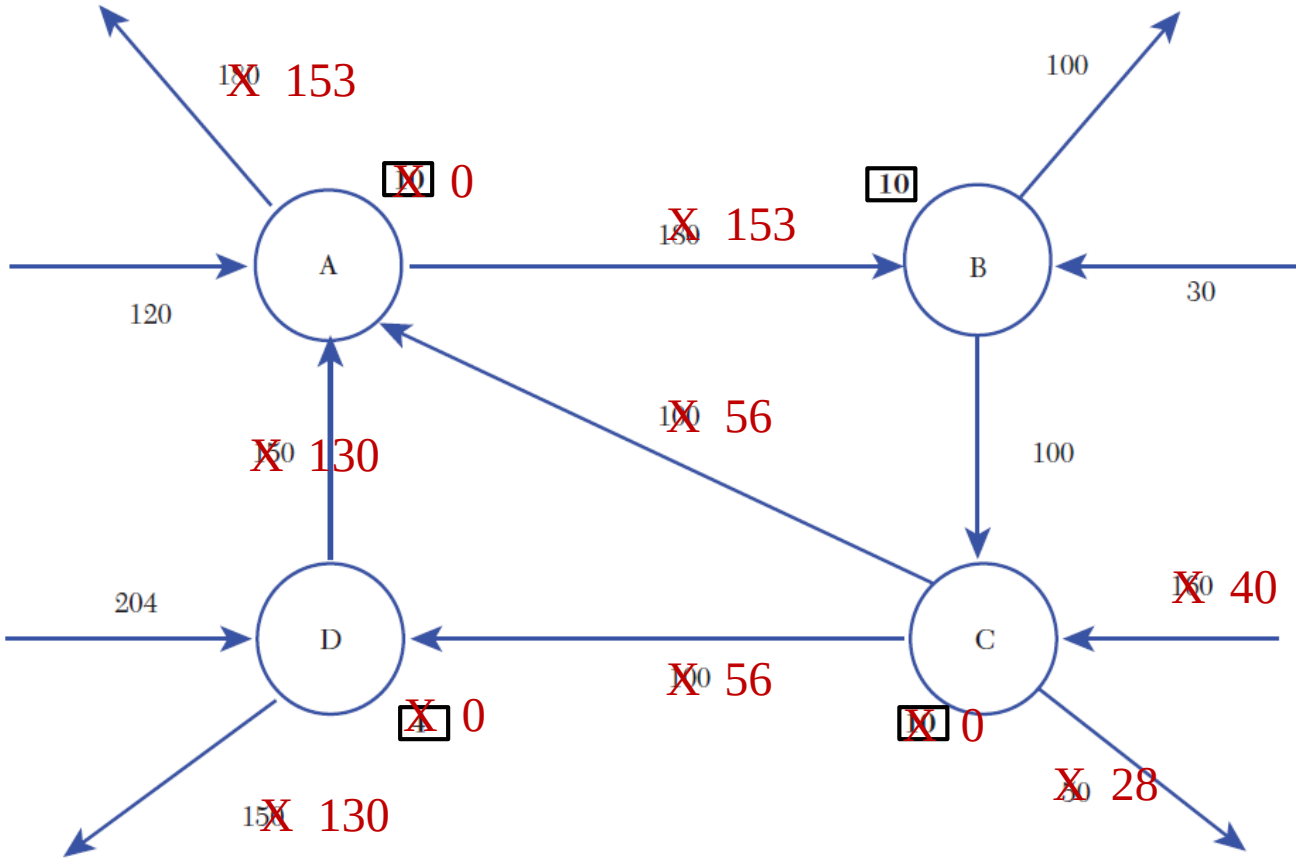
Figure 3. A Hypothetical Financial Network Showing Payments Due

Node C is wiped out:

140 received, 250 required

Makes pro rata payments to other nodes.

The Crisis Deepens



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Node B needs to pay 200

It only has 183

Our starting assumption that C would receive 100 from B was wrong!

Eisenberg-Noe (2001) Solves This Problem

- Find a consistent set of payments (and set of defaulting firms) that clears the network
- Payments may not be uniquely determined (defaulting nodes are)

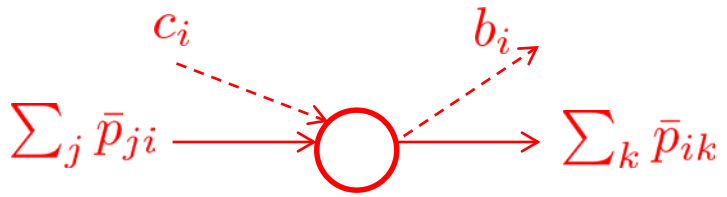
$$\text{Assets} = c_i + \sum_j \bar{p}_{ji}$$

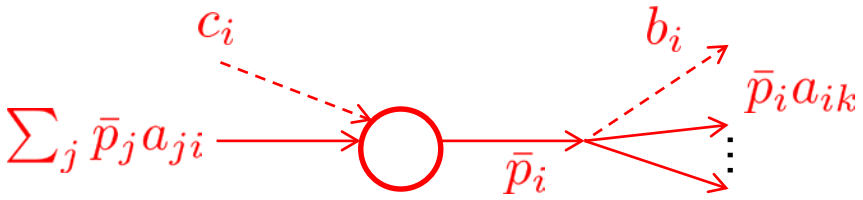
$$\text{Liabilities} = \bar{p}_i = b_i + \sum_k \bar{p}_{ik}$$

Relative liabilities matrix $A = (a_{ij})$

$$a_{ij} = \begin{cases} \bar{p}_{ij}/\bar{p}_i, & \bar{p}_i > 0; \\ 0 & \text{otherwise.} \end{cases}$$

We assume spectral radius of $A < 1$.

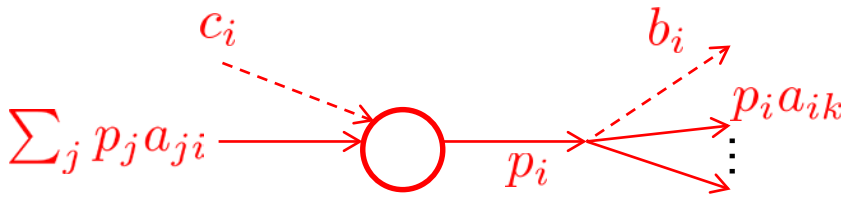




Clearing Payments

Distinguish promised payments $\bar{p}_i$ (face value) from actual payments (market values) p_i

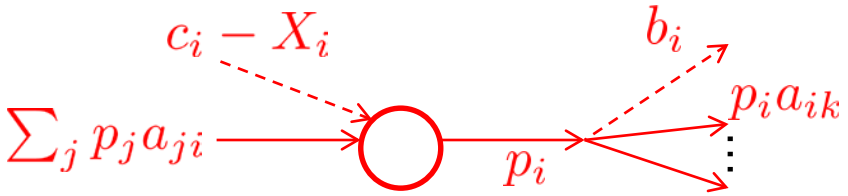
$$p_i = \bar{p}_i \wedge \left(c_i + \sum_j p_j a_{ji} \right)$$



Eisenberg-Noe give conditions for existence and uniqueness of a fixed point payment vector. This is automatic in our setting because A is strictly substochastic.

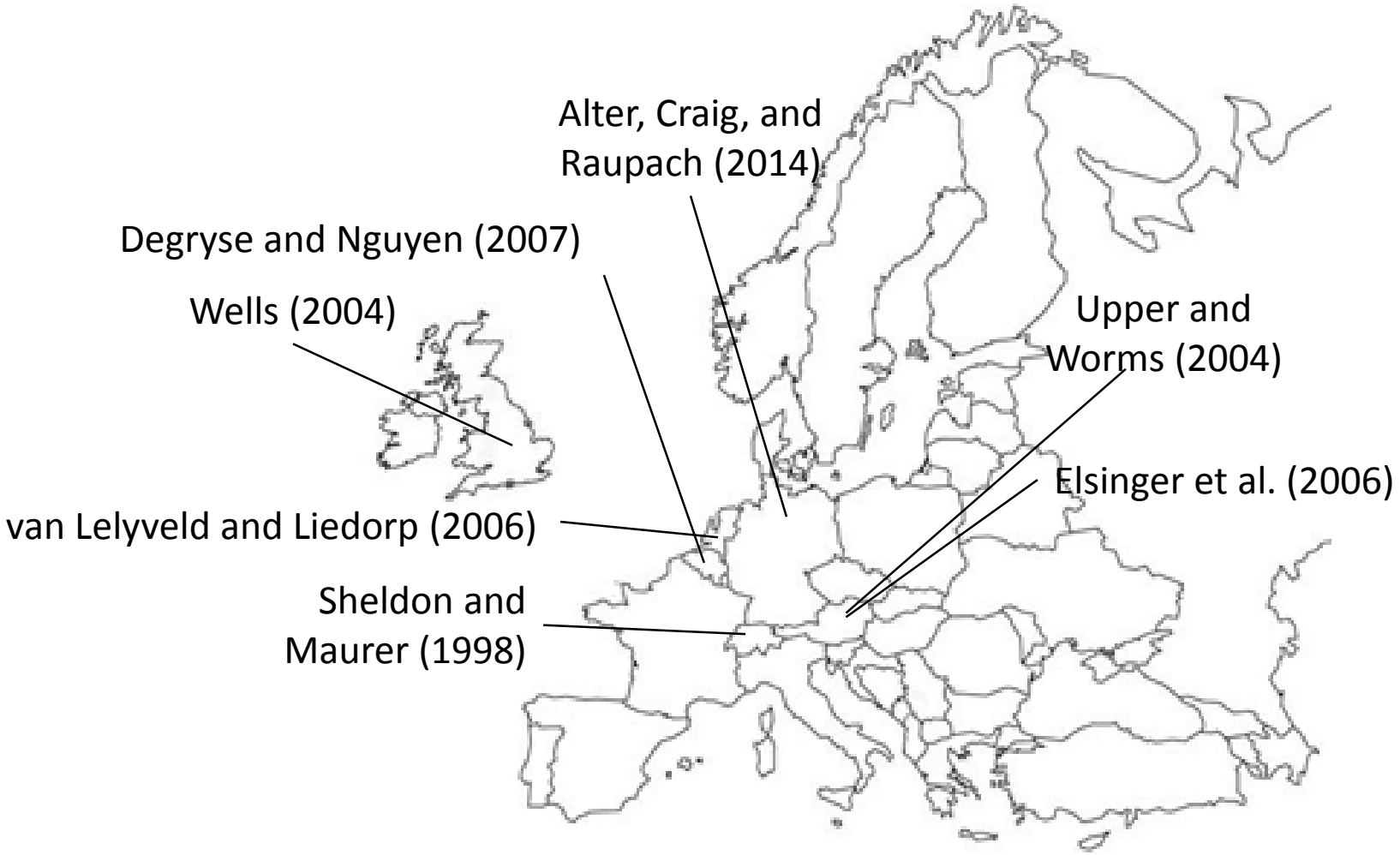
After a random shock X_i to outside assets c_i,

$$p_i = \bar{p}_i \wedge \left(c_i - X_i + \sum_j p_j a_{ji} \right)_+$$



Applications By Central Banks

- Many central banks have used variants of Eisenberg-Noe in stress-testing their banking systems
- Several studies pre-date the financial crisis
- Most found little evidence of systemic risk….



How Much Does Interconnectedness Matter?

- We would like to compare losses with and without the network
- (When we isolate the nodes, we replace in-network with claims with outside claims)
- We would like to make the comparison using public information (not detailed network structure)

- Total loss in the isolated system is

$$L^o = \sum_i X_i = \sum_i \text{shock to node } i\text{'s assets}$$

- Total loss in the interconnected system is

$$L = \sum_i \min\{X_i, \text{equity}_i\} + \sum_i \text{payment shortfall by node } i$$

Bounding the Network Effect (with Peyton Young)

Theorem: Suppose the relative shocks X_i/c_i have a common log-concave distribution. Let $\delta_i = P(X_i > w_i)$ and $\beta_{\max} = \max_i \beta_i$. Then

$$\frac{E[L]}{E[L^o]} \leq 1 + \frac{\sum_i \delta_i c_i}{(1 - \beta_{\max}) \sum_i c_i}$$

c_i = node i's outside assets

δ_i = marginal (direct) default probability

β_i = fraction of i's funding that comes from other financial institutions

- The network matters most when (1) large banks have high default probabilities or (2) banks rely on wholesale funding
- At reasonable parameters, the network effect adds only 2-6%
- All quantities can be approximated using public information

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Leverage, size, and systemic interconnectedness!

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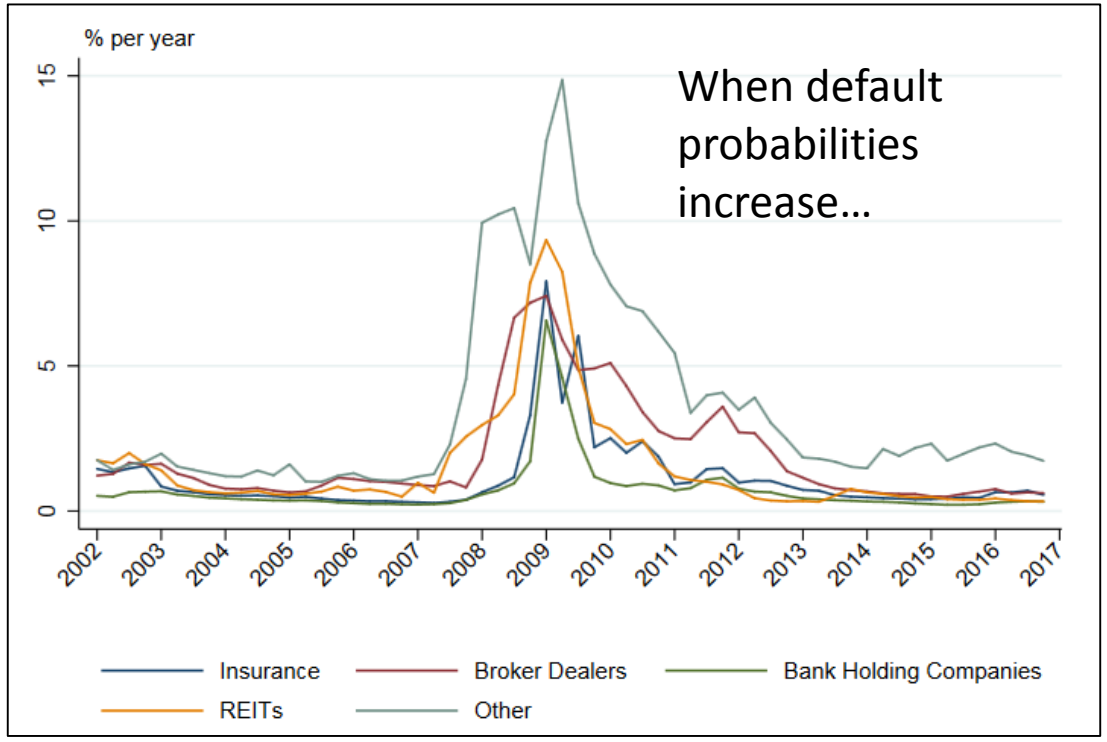
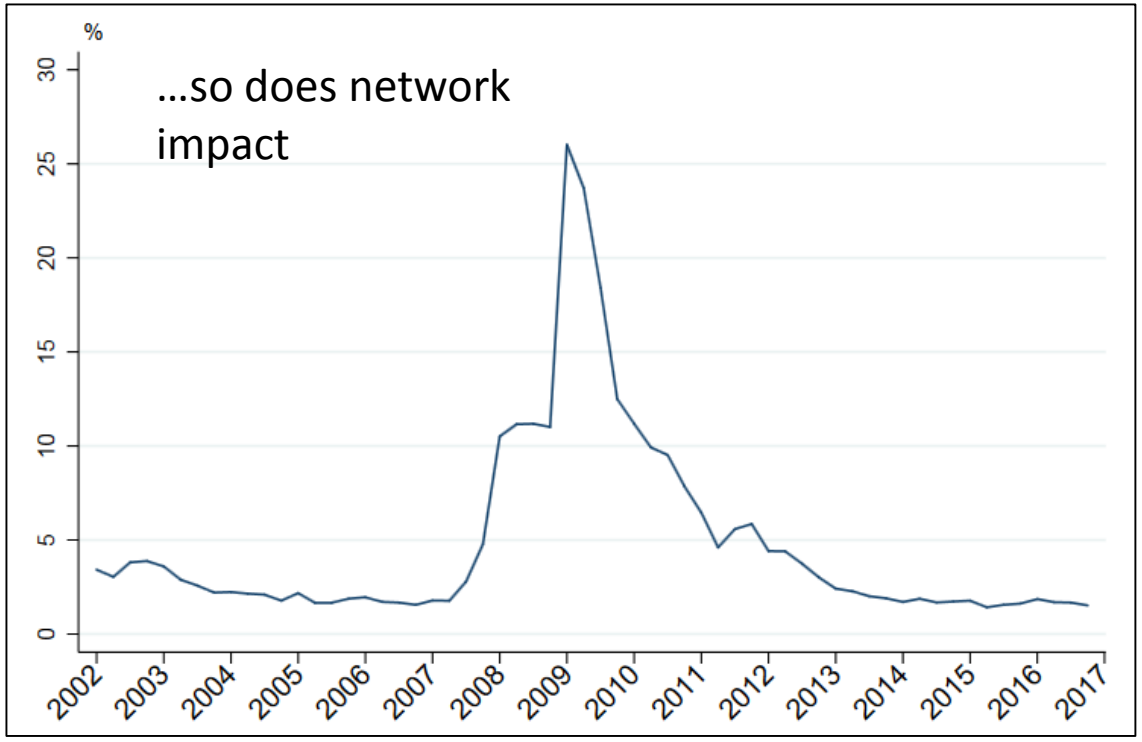
Empirical Estimates of the Network Bound

- Duarte and James (2017), Federal Reserve Bank of New York, estimated Glasserman-Young network bound for a network of banks, insurance companies, and broker-dealers





Should the Impact of Interconnectedness Be Greater?

- In other words, what is the Eisenberg-Noe model missing?

- Liquidity hoarding
  - In times of stress, firms pull back lending to other firms, amplifying stress (Allen and Gale 2000)

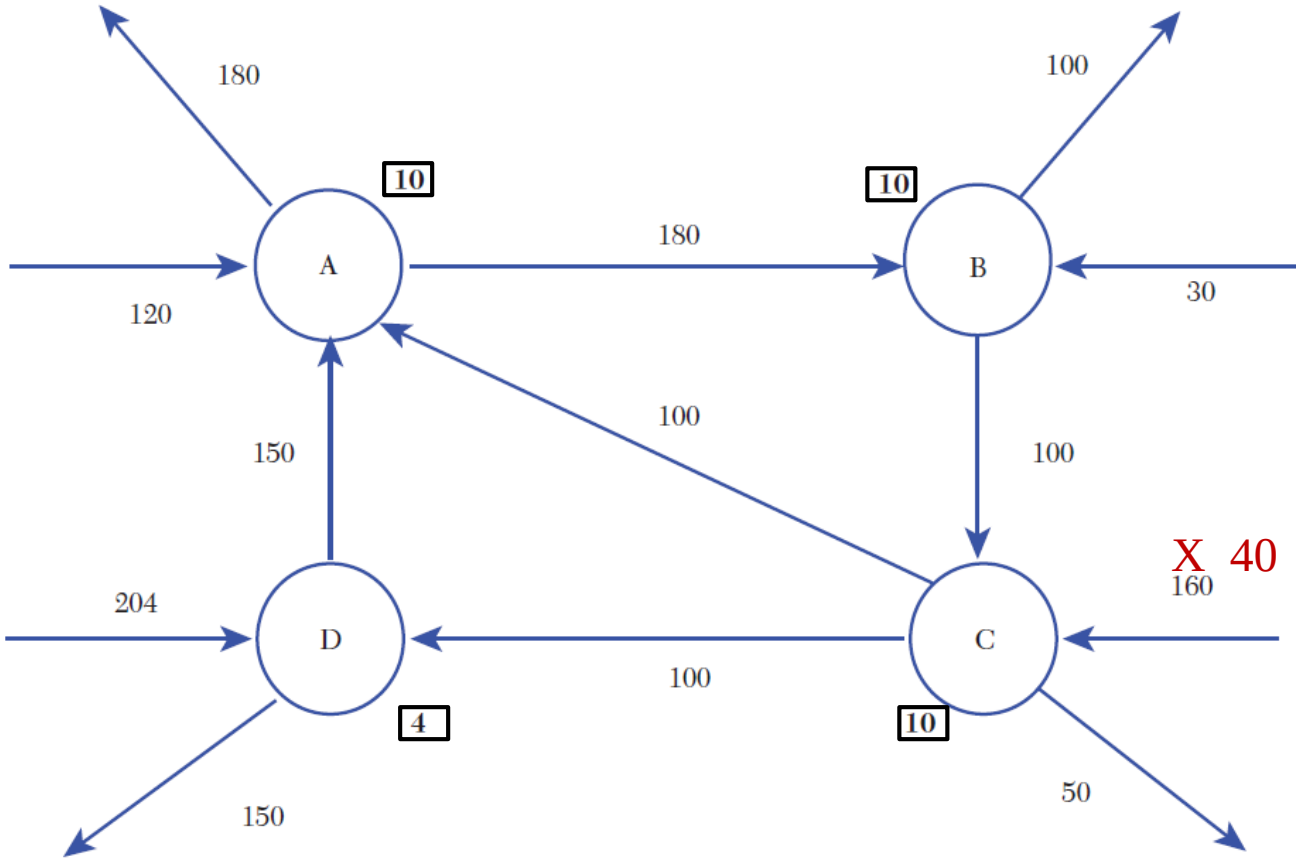
- Destruction of value at bankruptcy
  - Eisenberg-Noe measures payment shortfalls but no knock-on effects in loss of asset value at failure
  - Rogers and Veraart (2013) introduce discontinuous costs at bankruptcy

- Price contagion through fire sales
  - Sale of illiquid assets by troubled firm drives down prices of similar assets at other firms (e.g., subprime mortgage-backed securities); Cifuentes, Ferrucci, and Shin (2005)

Reversing the Arrows Turns a Default Cascade Into a Funding Run

Arrows show payment obligations

Values in boxes indicate net worth



Arrows show funding amounts

Values in boxes indicate cash balances

Initial shock is a withdrawal of funding

Bankruptcy Costs

- In Eisenberg-Noe, payments are continuous across the default boundary

$$p_i = \bar{p}_i \wedge \left(c_i + \sum_j p_j a_{ji} \right)$$

- Rogers and Veraart (2014) make it discontinuous; e.g.,

$$p_i = \begin{cases} \bar{p}_i, & \text{if solvent} \\ \alpha \left(c_i + \sum_j p_j a_{ji} \right), & \text{if bankrupt} \end{cases}$$

some $0 < \alpha < 1$, so $1 - \alpha$ is fraction of value lost at failure

- This leads to greater loss amplification as defaults cascade through the network

Integrating Fire Sales and Network Cascades

Cifuentes, Ferrucci, and Shin (2005)

- Banks need to meet a capital ratio
- Following a shock to asset value, bank needs to sell assets (delever) to restore ratio
- Selling assets drives down their price
- Lower price impairs capital ratio at other banks, which then need to sell assets
- All of this happens along with a possible spread of default through the network
- They conclude that liquidity buffers may be more effective than capital ratios

Eisenberg-Noe clearing payments

$$p_i = \bar{p}_i \wedge \left(c_i + \sum_j p_j a_{ji} \right)$$

become

$$p_i = \bar{p}_i \wedge \left(c_i(\pi) + \sum_j p_j a_{ji} \right)$$

where π = asset price

π is a decreasing function of amount sold by all banks

Solve for payments and price together

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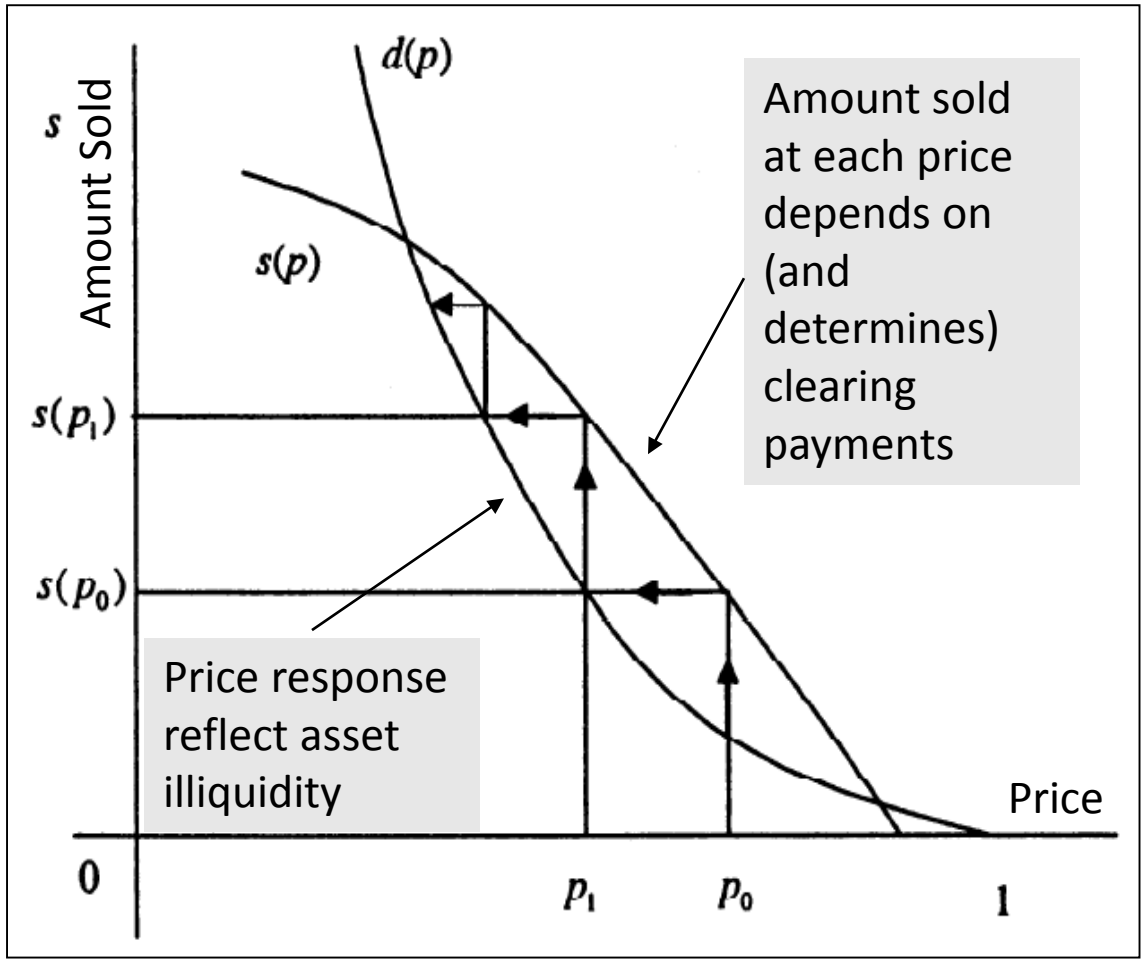

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- All of these channels operate simultaneously
- At the same time, market participants, regulators, and the public update their perceptions and adjust their behavior
- Network models have not reached this level of complexity
- In the meantime, they point to sensible constraints on leverage, size, and interconnectedness

Survey Article With Many References

- Glasserman, P. and Young, H.P. (2016) Contagion in financial networks. *Journal of Economic Literature 54*(3), pp.779-831

Thank you for your attention