Modeling Failure in Bank Networks

Preventing a Crisis

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Thesis Defense
January 12, 2017

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What is a (bank) network?

- Elements (nodes) that interact with each other (links)
- Bank networks capture how banks and other financial institutions are connected and can affect each other.
What do we mean by failure?

- Banks have Assets & Liabilities
- Assets – Liabilities = Equity

BANK FAILURE!!!!!
Why is this important?

• Can the connections between banks change the risk of bank failure?

• How could the whole financial system fail?
  – What causes cascading failures?

  **SYSTEMIC RISK**

• Can we add value to current policy making?
Why should physicists study bank networks?

• Bank network structures are complex, time-dependent and not well understood
  – Many interacting elements
  – Complex rules of interaction
  – Driven by stochastic processes

• Many banks rely on “quants” with physics/mathematics/computer science backgrounds

• Applying physics to the study of bank networks will help us understand cascading failures and may help us avoid economic disaster
Presentation Overview

• Summary of network models in banking

• Direct exposure network model
  – Federal Reserve Y-15 report case study

• Bipartite cascading failure network model
  – Venezuelan banking case study

• What have we learned from these models?
What kind of network model?!

• Type of network structure
  – Direct bank-to-bank network
  – Bipartite bank-asset network

• Type of nodes
  – All financial institutions
  – Only the biggest banks

• Type of links
  – Credit obligations
  – Asset similarity

• Other factors
  – Market liquidity, leverage ratios, etc.
  – Endogenous vs. exogenous shocks
What kind of network model?!

Network Approaches
- Direct
  - Interbank
  - CDS
- Indirect (price data)
  - Granger Causality
  - Portfolio Analysis
  - Variance Decomposition

Non-network Approaches
- PCA
- Regression
- Default Models
- Absorption Ratio/CRF
- Co-movement Coefficient
- Distress Probability

Gazi Kara, Mary Tian and Margaret Yellen
*Taxonomy of Studies on Interconnectedness*,
Direct Interbank Network

• Nodes = Banks
• Links = credit obligations between banks
  – Banks borrow funds from each other on a regular basis, mostly overnight lending
  – Banks also buy forms of insurance from other banks
  – If banks become distressed, they may not be able to fulfill their obligations to other banks

“Exposures” are the inverse of “obligations”
Direct Interbank Network

X

Z

Y
## Direct Interbank Network

<table>
<thead>
<tr>
<th></th>
<th>Bank X</th>
<th>Bank Y</th>
<th>Bank Z</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bank X</td>
<td>0</td>
<td>?</td>
<td>?</td>
</tr>
<tr>
<td>Bank Y</td>
<td>?</td>
<td>0</td>
<td>?</td>
</tr>
<tr>
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<td>?</td>
<td>?</td>
<td>0</td>
</tr>
</tbody>
</table>

\[ L \downarrow_{ij} = \text{obligation of bank } i \text{ to bank } j \]

\[ L_{ij} = \text{exposure of bank } j \text{ to bank } i \]

= obligation of bank to bank

= exposure of bank to bank
Estimating Bank Obligations

• We used data from Federal Reserve FR Y-15 report
  – This data set includes total assets and liabilities as well as total interbank obligations and exposures for the 33 largest US financial institutions

• Interbank obligations are the sums of the rows

• Interbank exposures are the sums of the columns of our network matrix
# Estimating Bank Obligations

<table>
<thead>
<tr>
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<td>?</td>
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</tr>
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<td>?</td>
</tr>
<tr>
<td>Bank Z</td>
<td>?</td>
<td>?</td>
<td>0</td>
</tr>
</tbody>
</table>

\[
\sum_{j} L_{ij} = o_{i} \\
\sum_{i} L_{ij} = e_{j} \\
\sum_{ij} L_{ij} = L \sum
\]

\[
\begin{array}{ccc}
10 & 6 & 4 \\
\end{array}
\]

\[= e\]

The total for each bank is shown in the rightmost column.
Estimating Bank Obligations

• Start with prior matrix

• Find L that minimizes Kullback-Leibler divergence (aka cross-entropy) within the constraints
  – This results in the most interconnected network possible

$$D_{KL}^*(L, U) = \sum_{i=1}^{n} \sum_{j=1}^{n} l_{ij} \log \left( \frac{l_{ij}}{u_{ij}} \right)$$

• We impose further constraints to alter the network structure
## Estimating Bank Obligations

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<td>?</td>
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</table>

Total: 10, 6, 4
## Estimating Bank Obligations

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<th>Bank Y</th>
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<tbody>
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<td>Bank Z</td>
<td>3.5</td>
<td>2.1</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>10</td>
<td>6</td>
<td>4</td>
</tr>
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Estimating Bank Obligations

<table>
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<th>Bank Y</th>
<th>Bank Z</th>
</tr>
</thead>
<tbody>
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<td>5.69</td>
<td>1.31</td>
<td>0</td>
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</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>10</th>
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</table>
Can the banks cover their obligations?

• If payments are made on all interbank obligations, will any banks fail?

then the bank fails

• If a bank fails then it can’t completely fulfill its obligations

• Banks “exposed” to that bank won’t receive full payments

• Now those banks may fail, even if $equity_{\downarrow i} + \sum_{j}^{\uparrow \downarrow} L_{\downarrow ij} - \sum_{j}^{\uparrow \downarrow} L_{\downarrow ij} > 0$, and we will have cascading failures
Measuring systemic risk

• How many banks fail? How many cascading failures?
  – For the FR Y-15 US bank data, we find that
    • 3 of the 33 banks would fail initially (BNY MELLON, AMEX, STATE STREET)
    • 1 due to a cascading failure (DEUTSCHE BANK)

• How much money is lost in the system due to bankruptcies?
  – $292.4M out of $2.38B (12.3%) in total interbank obligations

• How do these values change with our assumptions about interconnectedness?

• What if we shock the system?
  – What if asset values drop across the system?
  – What if a bank unexpectedly fails? How does that affect the rest of the system?
# Changing the Network Structure

<table>
<thead>
<tr>
<th></th>
<th>Bank W</th>
<th>Bank X</th>
<th>Bank Y</th>
<th>Bank Z</th>
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</thead>
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</tr>
<tr>
<td>Bank X</td>
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<td>0.90</td>
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<tr>
<td>Bank Y</td>
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<td>1.64</td>
<td>0</td>
<td>1.36</td>
</tr>
<tr>
<td>Bank Z</td>
<td>2.94</td>
<td>1.21</td>
<td>0.86</td>
<td>0</td>
</tr>
</tbody>
</table>

| Total | 10     | 6      | 4      | 5      |
## Changing the Network Structure

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<td>0</td>
</tr>
</tbody>
</table>

| Total | 10     | 6      | 4      | 5      |

- Bank W: 8
- Bank X: 5
- Bank Y: 7
- Bank Z: 5
# Changing the Network Structure

<table>
<thead>
<tr>
<th>Bank</th>
<th>W</th>
<th>X</th>
<th>Y</th>
<th>Z</th>
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</thead>
<tbody>
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<td>0.30</td>
<td>2.12</td>
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<tr>
<td>Bank Y</td>
<td>3.52</td>
<td>0.60</td>
<td>0</td>
<td>2.88</td>
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<tr>
<td>Bank Z</td>
<td>3.89</td>
<td>0.66</td>
<td>0.45</td>
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</tbody>
</table>

**Counts:**
- Bank W: 8
- Bank X: 5
- Bank Y: 7
- Bank Z: 5

**Total:** 10 6 4 5
Measuring systemic risk
Network Structure

Risk Sensitivity to Interconnectedness

Value Lost to Bankruptcies ($M)

% of Links Broken

0  100  200  300  400  500  600  700
Measuring systemic risk
Network Structure

Risk Sensitivity to Interconnectedness

![Graph showing the relationship between percentage of links broken and average value lost to bankruptcies.](image)
Bipartite Bank-Asset Network

• Nodes = Banks & Assets Classes
  – Two types of nodes
• Link = asset type is owned by a bank
  – Links are only between bank nodes & asset nodes
Bipartite Bank-Asset Network

Bank A

- Commercial Credit
- Treasury Bonds
- Mortgage Loans
- Private Securities
- Vehicle Loans
- Agriculture Bonds

Mortgage Loans

- Bank A
- Bank B
- Bank C
- Bank D

\[ B_i = \text{total asset value of bank } i \]

\[ A_m = \text{total value of asset } m \text{ in system} \]

\[ B_{i,m} = \text{value of asset } m \text{ owned by bank } i \]
1. Initial shock to chosen asset class

2. Devalue bank assets correspondingly

3. Check for bankruptcies
   - If none, then we’re done
   - If assets < liabilities, then the bank fails

4. Devalue assets owned by failed banks

5. Return to step 2

Cascading Failure Model

\[ B_i = \text{total asset value of bank } i \]

\[ A_m = \text{total value of asset } m \text{ in system} \]

\[ B_{i,m} = \text{value of asset } m \text{ owned by bank } i \]

\[ m^* = \text{shocked asset} \]

\[ p = \text{fraction of shocked asset remaining} \]

\[ \alpha = \text{liquidity parameter, aka fire-sale effect} \]
Sensitivity to $\alpha$ & $p$

$\chi(\alpha,p,m) =$ fraction of surviving banks

12/2005

12/2013

Commercial Credit  BCV Bonds
Stable sensitivity
Commercial Credits

6/2005
Unstable sensitivity
BCV Bonds

6/2005
Very unstable sensitivity
Treasury Notes

6/2005
Failure by asset size

\( p = 0.6, \alpha = 0.1 \)

\( \chi \)

\( \beta \)

\( \beta = \text{relative size of shocked asset} \)
Failure by asset size

$p=0.6, \alpha = 0.2$

$\chi$ = relative size of shocked asset

$\beta$ = relative size of shocked asset
What should you take away?

- Greater interconnectedness tends to result in a more resilient system
- Risk of systemic failure is sensitive to small changes in shock size and the fire-sale effect
- The size of a shock and level of liquidity that will cause systemic failure can change abruptly month-to-month and needs to be monitored
Why is this important?

• How do the connections between banks change the risk of bank failure?
  – More interconnectedness tends to mean less systemic risk, but not always so

• How could the whole financial system fail?
  – Shocks in prices of widely held assets, i.e. mortgages, bonds, etc.

• Can we add value to current policy making?
  – We have tools help monitor systemic sensitivity to adverse scenarios, i.e. a new mortgage crisis
Econophysics publications


Thank you!

- Thanks to Gene Stanley
- Thanks to Irena Vodenska, Sary Levy-Carciente, Dror Kenett, Shlomo Havlin & all my collaborators
- Thanks to my committee members
- Thanks to all who listened to my practice talks
- Thanks to Mirtha Cabello!!!!!

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Measuring systemic risk
Asset Shocks

Risk Sensitivity to Global Asset Shocks

Default Rate (%) vs. % of Links Broken

Value Lost to Bankruptcies ($M) vs. Shock to Assets (%)
# Asset & Bank Types

<table>
<thead>
<tr>
<th>Asset Types</th>
<th>Bank Types</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cash &amp; Cash Equivalents</td>
<td>Commercial banking</td>
</tr>
<tr>
<td>Credit</td>
<td>Universal banking</td>
</tr>
<tr>
<td>Commercial credit</td>
<td>Investment banking</td>
</tr>
<tr>
<td>Vehicle credit</td>
<td>Savings and loan institutions</td>
</tr>
<tr>
<td>Credit cards</td>
<td>Mortgage banking</td>
</tr>
<tr>
<td>Mortgage loans</td>
<td>Leasing institutions</td>
</tr>
<tr>
<td>Microcredit</td>
<td>Money market funds</td>
</tr>
<tr>
<td>Agriculture credit</td>
<td>Micro-finance banking</td>
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<tr>
<td>Tourism credit</td>
<td>Development banking</td>
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<td>Manufacturing credit</td>
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<td>Securities</td>
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<td>Private securities</td>
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<tr>
<td>Treasury notes</td>
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</tr>
<tr>
<td>Treasury bonds</td>
<td></td>
</tr>
<tr>
<td>Public national debt</td>
<td></td>
</tr>
<tr>
<td>BCV bonds</td>
<td></td>
</tr>
<tr>
<td>Agriculture bonds</td>
<td></td>
</tr>
</tbody>
</table>
A brief history of the Venezuelan banking system

- Leasing companies
- Mortgage banks
- Investment banks
- Commercial banks
- Universal banks
- Credit
- Sec.
- Cash
- Universal banks
- Credit
- Sec.
- Cash

1/1998

12/2013
Results from Huang, et al. (2013)

• Was able to correctly identify many of the banks that failed following the 2008 crash
• Sensitivity to commercial (not residential as many people said) real estate asset values were primarily responsible for 2008 crash
• Can be used as a stress testing tool to prevent future crashes
Venezuelan case study

• Cons
  – No crash with which to tune parameters
  – Much smaller financial system
    • Less global impact
• Pros
  – Longitudinal data (monthly 1998-2013)
  – Much smaller financial system
    • We can easily look at a large parameter space
Failure by asset size

By year

χ

By asset

χ

β = relative size of shocked asset  p=0.6, α= 0.1

p=0.6, α= 0.2
Sensitivity to liquidity and relative asset size

\( \alpha_{\text{crit}} \) – smallest \( \alpha \) such that fewer than 20% of banks survive

\[
\alpha_{\text{crit}}(p) = \alpha \mid (\chi(p, \alpha) \leq 0.20 \ \& \ \chi(p + 0.01, \alpha) > 0.20)
\]

\( \beta \) – relative size of shocked asset

\[
\beta_m = \frac{A_m}{\sum_i A_i}
\]
Asset size and concentration with sensitivity to liquidity

\[ \text{HHI} = \sum_i \left( \frac{B_{i,m}}{A_m} \right)^2 \]

\( \alpha_{\text{crit}} \)

\( \beta \)

HHI – measure of concentration of shocked asset

commercial credit, \( p=0.70 \)
Asset size and concentration with sensitivity to liquidity

HHI – measure of concentration of shocked asset

\[ \text{HHI}_m = \sum_i \left( \frac{B_{i,m}}{A_m} \right)^2 \]
Asset size matters
Correlation of $a_{\text{crit}}$ vs $\beta$
Asset distribution matters

Correlation of $\alpha_{\text{crit}}$ vs HHI
Comparing to traditional risk measures

Average fail order

\[ \alpha = 0.10, \ p = 0.70, \ \text{all assets} \]

Debt-to-equity ratio
<table>
<thead>
<tr>
<th>$p$</th>
<th>$\alpha = 0.0$</th>
<th>$\alpha = 0.10$</th>
<th>$\alpha = 0.20$</th>
<th>$\alpha = 0.30$</th>
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<tr>
<td>0.70</td>
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<td><img src="image7.png" alt="Image" /></td>
<td><img src="image8.png" alt="Image" /></td>
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<tr>
<td>0.50</td>
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<tr>
<td>0.20</td>
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</table>
Sensitivity to $\alpha$ & $p$

$\chi(\alpha, p, m) = \frac{\text{fraction of surviving banks}}{12/2005}$

$\chi(\alpha, p, m) = \frac{\text{fraction of surviving banks}}{12/2013}$

Commercial Credit

BCV Bonds