Modeling financial system vulnerability through heterogeneous adaptive learning agent models

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Figure: One of the important consequences of the 2008 financial crisis was the realization that the current US financial system is full of vulnerability. Source: Reinhart and Rogoff (2011)
Motivation: We are vulnerable more than ever before?

- Most of the current literature focus on either highly stylized network models or empirical examinations of limited observations in some countries to gain insight on counterparty risk and liquidity risk contagion - [Gai et al., 2011]

- During the 2007-09 Financial Crisis, the interbank market behavior suggested a heightened concern for counterparty risk that reduced liquidity and increased the cost of financing for weaker banks - [Afonso et al., 2014]

- Bank’s autonomous behaviors are not represented well in a pure optimization theoretical framework, which has led to a series of attempts to study endogenous interbank network formation models - [Liu et al., 2017]
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- **Whatever can go wrong, will go wrong, and faster and bigger when computers are involved** - Andrew Lo 2017 [Sloan MIT].
Motivation: How can we trust the increasingly complex and vulnerable systems?

Threats to financial stability can arise from surprising quarters
- Levin 2015.
An agent-based approach to model how autonomous agents learn and adapt to the system changes, and show how risk averse behaviors change the network structures/system behaviors - emergence.

We model banks’ lending and borrowing behaviors according to statistical patterns of individual banks and general behavior patterns from the empirical findings. Not all agents are rational; do not assume any equilibrium.

We probe the system vulnerability through both endogenous behaviors and exogenous shocks through repeated Monte Carlo simulation by comparing networks pre and post financial crisis, and system under stress.
Financial reports are one of the key information sources that disclose banks’ financial fundamentals and business conditions.

The Federal Reserve, FDIC, and OCC require all U.S. regulated banks to submit quarterly reports known as Federal Financial Institutions Examination Council Reports of Condition and Income.

Similar to regulators that rely on balance sheets to monitor banks’ liquidity status and banking system structures, we use balance sheets data from March, 2001 to December, 2014, covering around 10,000 banks.
# Bank Balance Sheet Data

## Table: Description of the bank balance sheet

<table>
<thead>
<tr>
<th>Assets, $A$</th>
<th>Liabilities, $L$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Overnight lending: federal funds, $ON^l$</td>
<td>Overnight borrowing: federal funds, $ON^b$</td>
</tr>
<tr>
<td>Short-term lending: federal securities, $ST^l$</td>
<td>Short-term borrowing: federal securities, $ST^b$</td>
</tr>
<tr>
<td>Long-term lending: loans due from banks, $LT^l$</td>
<td>Long-term borrowing: loans due to banks, $LT^b$</td>
</tr>
<tr>
<td>Cash and balance due, $C$</td>
<td>Other liabilities, $OL$</td>
</tr>
<tr>
<td>Other assets, $OA$</td>
<td>Equity, $E$</td>
</tr>
</tbody>
</table>

**Notes:** This description of a bank’s balance sheet focuses on major bank lending and borrowing channels, i.e. overnight, short-term, and long-term markets. The rest of the balance sheet is condensed into cash or other assets or liabilities.
Multi-agent interbank lending framework

- The model initializes a lending network with 6600 banks linked by interbank debts.

- This initial network is calculated by balance sheet data in 2006 using maximum entropy approach for solving the bilateral exposure problem - [Upper and Worms, 2004].

- Then the system will reorganize itself through the multi-agent learning process.
Heterogenous learning agent interbank lending framework

We categorize two types of banks and three types of debts based on the empirical analysis from the balance sheet data ([Cocco et al., 2009], [Roukny et al. 2014], [Afonso et al., 2014]).

**Table: Interbank lending network setting**

<table>
<thead>
<tr>
<th>Nodes</th>
<th>Large banks</th>
<th>Small banks</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>The largest four domestic banks: Bank of America, Citibank, J.P. Morgan Chase Banks, and Wells Fargo Bank</td>
<td>Other banks</td>
</tr>
<tr>
<td>Links</td>
<td>Overnight debts</td>
<td>Federal funds, usually expire overnight</td>
</tr>
<tr>
<td></td>
<td>Short-term debts</td>
<td>Federal securities, usually expire within 1 month</td>
</tr>
<tr>
<td></td>
<td>Long-term debts</td>
<td>Loans expire less than 1 year</td>
</tr>
</tbody>
</table>
In every iteration, banks first process payments to existing debts and we adopt an iterative clearing vector algorithm to clear payments - [Eisenberg and Noe, 2001].

During the clearing process, banks may face liquidity or solvency issue that results in defaulting (equation (1) and (2)).

\[ E_i(t) < A_i(t) - L_i(t) \]  \hspace{1cm} (1)
\[ C_i(t) < ON_i^P(t) + ST_i^P(t) + LT_i^P(t) \]  \hspace{1cm} (2)

The lenders realize write-down for debts with defaulting banks according to the Eisenburg-Noe algorithms pro rata loss distribution method.
In this system, banks target at a series of balance sheet ratios (see Table 3), and these ratios are associated with banks' policies of lending and borrowing.

**Table:** Bank balance sheet ratio

<table>
<thead>
<tr>
<th></th>
<th>$E_i$</th>
<th>$E_i$</th>
<th>$ON_i^l$</th>
<th>$ON_i^b$</th>
<th>$ON_i$</th>
<th>$L_i$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Equity Multiplier</td>
<td>$A_i$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Overnight Lending, Borrowing Ratio</td>
<td></td>
<td></td>
<td>$A_i$</td>
<td>$A_i$</td>
<td>$L_i$</td>
<td>$L_i$</td>
</tr>
<tr>
<td>Short-term Lending, Borrowing Ratio</td>
<td></td>
<td></td>
<td>$A_i$</td>
<td>$A_i$</td>
<td>$L_i$</td>
<td>$L_i$</td>
</tr>
<tr>
<td>Long-term Lending, Borrowing Ratio</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
What is Reinforcement Learning?

- Reinforcement learning is a learning method that allows agents to learn and determine the ideal action based on past experience.
- Agents learn by receiving reinforcement signals (reward or punishment) by interacting with the environment.
- **Objective:** Select actions such that the sum of all expected future reward is maximized.
What is Reinforcement Learning?

There are three elements that drive the interaction between an agent and the environment: state, action, and reward.

- **States:**
  - Information used by agents to determine what to do next
  - Function of history that contains past observations, actions, and rewards

- **Actions:** Determined by either the value function, policy, or model of the agent
  - Policy represents the agents behavior - a map from state to action
  - Value function evaluates how good it is for the agent to be in a given state

- **Rewards:** A feedback signal to indicate how well the agent did in this iteration
What is Reinforcement Learning?

**Figure:** Agent environment interaction in reinforcement learning
Banks keep track of two scores for all other banks in order to pick the counterparties for new debts: a size score, $S^{\text{reputation}}$, and a relationship score, $S^{\text{relation}}$.

$S^{\text{reputation}}$ is calibrated through the comparison of bank capitalization, asset quality, NPL with existing counterparties

$$S_{i,j}^{\text{reputation}}(t) = \log A_j(t) - \frac{\sum_{k,k\neq i} \log A_k(t-1) \mathbb{I}_{i,k}(t-1)}{\sum_{k,k\neq i} \mathbb{I}_{i,k}(t-1)}$$

where $S_{i,j}^{\text{reputation}}(t)$ is the size score of bank $j$ evaluated by bank $i$ on the period $t$, $A_j$ is the total assets of bank $j$, $\mathbb{I}_{i,k}(t)$ is a binary variable for keeping track previous debt obligations.
The relationship score, $S_{\text{relation}}$, captures the preference of continuing business with existing counterparties.

The score will be updated upon receiving the reinforcement signal from the lending and borrowing actions a bank makes in each iteration by using **temporal difference learning**.

In addition, banks also hold private information about their own target ratios and evaluate the status of their balance sheet to help guide the lending and borrowing policy.
Bank’s lending and borrowing policy

Each bank with space in its $ON^l$, $LT^l$, or $ST^l$ follows a similar scoring system as described in equation (4 and 5).

$$S_{i,j}^{\text{total}} = \omega S_{i,j}^{\text{relation}} + (1 - \omega) S_{i,j}^{\text{reputation}}$$  \hspace{1cm} (4)

where $S_{i,j}^{\text{total}}$ is the score that borrower $i$ assigns to lender $j$. It is the weighted average of relationship score and size score of bank $j$. We set equal weights to these scores so that $\omega = 0.5$.

$$p(S_{i,j}^{\text{total}}) = \frac{1}{1 + \exp(\alpha + \beta \times S_{i,j}^{\text{total}})}$$  \hspace{1cm} (5)

$p(S_{i,j}^{\text{total}})$ is a S-shaped function that represents the probability that borrower $i$ lends to lender $j$. $\alpha$ and $\beta$ denote the bank’s risk tolerance level.
Temporal difference learning

- Temporal difference (TD(\(\lambda\))) is a learning method through which an agent learns to measure the total amount of reward expected over the future.

- The TD(\(\lambda\)) algorithm combines the characteristics of both the Monte Carlo method and dynamic programming.

\[
V(s_t) = V(s_t) + \alpha[r_{t+1} + \gamma V(s_{t+1}) - V(s_t)]
\]  

(6)

\(V(s_t)\) is the estimate of expected sum of discounted rewards at time \(t\), \(r_{t+1}\) denotes the observed reward, \(\alpha\) is the learning rate, and \(\gamma\) is a discount factor for \(V(s_{t+1})\).
Convergence of temporal difference learning

We validate the use of *TD* learning by investigating the convergence of relationship score (the TD updating target) over time.

**Figure:** Learning convergence of TD target
Table: U.S. Federal Funds Market Interbank Network Property Comparison (100 simulations)

<table>
<thead>
<tr>
<th></th>
<th>Average In-Degree</th>
<th>Average Out-Degree</th>
<th>Clustering Coefficient</th>
<th>Power Law</th>
</tr>
</thead>
<tbody>
<tr>
<td>U.S. Fed Funds Market</td>
<td>9.3</td>
<td>19.1</td>
<td>0.28</td>
<td>2.00</td>
</tr>
<tr>
<td>System Output</td>
<td>10.39</td>
<td>17.14</td>
<td>0.21</td>
<td>2.34</td>
</tr>
</tbody>
</table>

Notes: This table lists the key network measures between the real U.S. federal funds market and the simulation results. For the In-Degree and Out-Degree measure we used the GSCCD - giant strongly connected component reported in Bech and Atalay 2010 as it reflects the interbank market mostly. Source: Bech and Atalay 2010; Authors’ calculations.
Figure: Interbank network degree distribution. Both in-degree and out-degree are heavily skewed right, indicating that the majority of bank agents have few established relationships. Moreover, we observe power-law decaying pattern in the in-degree is distribution.
### Table: Interbank network topology.

<table>
<thead>
<tr>
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<th>Clustering coefficient</th>
<th>Power law</th>
<th>Average path</th>
</tr>
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<tbody>
<tr>
<td><strong>Overnight</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Loose Policy</td>
<td>15.12</td>
<td>0.35</td>
<td>2.39</td>
<td>2.34</td>
</tr>
<tr>
<td>Risk-Averse Policy</td>
<td>11.51</td>
<td>0.19</td>
<td>2.42</td>
<td>2.66</td>
</tr>
<tr>
<td><strong>Short-term</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Loose Policy</td>
<td>1.04</td>
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<td>Risk-Averse Policy</td>
<td>2.42</td>
<td>0.57</td>
<td>2.15</td>
<td>2.28</td>
</tr>
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Figure: Interbank network structures with a loose-lending policy at $\alpha = -1$ (Right) and a risk-averse policy at $\alpha = 5$ (Left). In both plots, we labeled the four large bank agents as "1,2,3,4" because empirical studies have suggested that they tend to establish more relationships than other banks.
Figure: Risk preference $\alpha$ vs. in-degree and out-degree. These plots are consistent with our finding of asymmetric distributions for lending and borrowing. They also show that with an increasing $\alpha$, it becomes harder for banks to find lenders such that the in-degree is decreasing with a tighter confidence interval.
Figure: Risk Preference $\alpha$ vs. Clustering coefficient and average min path. The above plots show that when banks become more averse to lending to other banks, the network becomes less clustered and connected.
We simulate the banking system dynamics such that we can take advantage of the agent based framework.
The 2008-2009 Financial Crisis

- We simulate the banking system dynamics such that we can take advantage of the agent based framework.
- The experiment is designed to replicate the financial crisis.
- Triggering exogenous shocks to bank the balance sheet for 21 periods; matching with the Housing Price Index during 2007 Q1 to 2014 Q1.
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We compare the pre-crisis era to the post-crisis era interbank lending networks.

We can see the post-crisis network is relatively less dense.
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pre-Crisis</td>
<td>14.78</td>
<td>0.36</td>
<td>2.39</td>
<td>2.11</td>
</tr>
<tr>
<td>Post-Crisis</td>
<td>5.33</td>
<td>0.13</td>
<td>2.45</td>
<td>3.09</td>
</tr>
<tr>
<td><strong>Short-term</strong></td>
<td></td>
<td></td>
<td></td>
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Table: Interbank Network Topology

The overnight network is where the greatest change is observable, as one might predict.
We compare the pre-crisis era to the post-crisis era interbank lending networks and run a similar real estate shock.

We observe that the number of failed banks drops from 500 to 370, a 25% decrease at a steady state. This bank failure pattern shift can be explained by the network topological change, consistent with [Allen and Gale, 2000] work.
Conclusions

- This study proposes a dynamic interbank market model with learning agents to reconstruct interbank networks based on bank performance data and behavioral patterns.

- Result shows that as banks tighten their lending policies, the network becomes more sparse and thus more concentrated on which banks lend to. As a result, the interbank network is less at risk to concerns of contagion.

- Bank level performance and behavior patterns driven models provide a means of recovering the latent interbank exposures networks.

- ABM methodology provides a tool for central banks and regulators to conduct system level stress tests and cost-benefit analysis for policy.

- We show through this model that the U.S. banking system has improved in terms its robustness and resilience to the known shocks.
Current & Future Work

- The 9-11 terror attack on the World Trade Center in 2001. [Fleming and Garbade, 2002] describes the enormous increase in the number of failed transactions (US $1.7 billion to US $190 billion a day) in the Treasury market after the 9-11 attack. These failures were associated with the destruction of electronic trade records, physical communication and power facilities.

- A 2015 study of the financial impact of a hypothetical electric grid failure scenario in the US \(^1\) suggests that major cyber-attacks can have cascading effects that trigger much greater economic losses than just the power outage or electric infrastructure damage.

- In February 2013, the President issued Presidential Policy Directive 21 (PPD-21), Critical Infrastructure Security and Resilience, which explicitly calls for an update to the National Infrastructure Protection Plan (NIPP). It includes financial services as one of the 16 sectors of national critical infrastructures.
Financial markets infrastructure (FMI) is fundamental to modern economies for providing platforms and interfaces by which business operations are financed to support sustained growth, financial institutions manage their risks, and wealth of nations gets managed for current investment and future consumption.

We identify four types of exogenous shocks/extreme events to examine FMI vulnerability: a) operational errors which define market anomalies or operational risks, such as the trigger of the 2010 flash crash; b) cyber attacks such as February 2016 Bangladesh’s Central Bank hacking; c) terrorist attacks such as 9-11 terrorist attack on the World Trade Center; d) natural disasters such as 2012 Hurricane Sandy’s devastating effects on NYC.


When the back office moved to the front burner: Settlement fails in the treasury market after september 11.

Complexity, concentration and contagion.

Interbank contagion: An agent-based model approach to endogenously formed networks.
*Journal of Banking & Finance.*

Estimating bilateral exposures in the German interbank market: Is there a danger of contagion?