Topics on Interconnectedness and Regulation of Financial Networks

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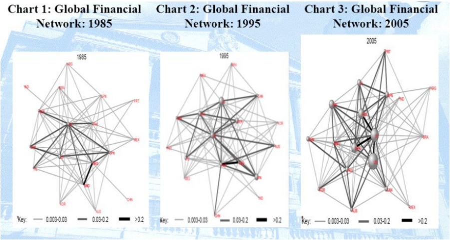
Roadmap

Motivation

- By the onset of the financial crisis of 2008, the US financial system had become increasingly more interconnected.

- Complexity of financial markets has made understanding stability and regulation a challenging problem.
    - Diversified exposures: the failure of one institution has impacts on the failures of others.
    - Complex lending relations: interbank and overnight lending, securitized lending such as repo market, derivatives markets.



- Does the study of financial networks help us better understand stability?

What We Do

- Study the link between interconnectedness and systemic risk
  - what is the optimal amount of interconnectedness?
  - does complexity help or hurt systemic vulnerabilities?
  - what do we formally mean when we say "interconnected?"

- Can we implement regulation to control how interconnected the financial network is?

- How does regulation affect the network and what are the implications for systemic risk?

- Today:
  - three (3) potential projects
  - simple examples to illustrate phenomena
  - highlight main mechanisms
  - discussion of projects going forward

Overview

(a) *Robust Regulation of Dynamic Financial Networks*

(b) *Derivatives Networks and Systemic Risk*

(c) *Measuring Interconnectedness*

- All seek to develop a better understanding of how liquidity crises, interconnectedness, and regulation affect financial stability.
- Will discuss (a) in detail, some of (b), and only very basics of (c). Happy to discuss in greater detail after presentation.
- **Very preliminary work**

Robust Regulation of Dynamic Networks

- Banks receive noisy signals about the strength of other banks' fundamentals, and then must decide how much to invest in cash and other assets.
- When signals across banks are highly correlated, overlapping portfolios are highly concentrated. Banks are susceptible to the same idiosyncratic shocks.
- If signals generate more disagreement, the financial network evolves in a way that leads to more diversification. No banks are exposed to just one or two idiosyncratic shocks.
- What are the avenues for regulatory policy?
  1. Protective policy: Require banks to hold more cash, which provides a buffer for idiosyncratic shocks.
  2. Preventative policy: Mandate more highly-connected institutions to hold more cash. This changes the network dynamics because banks realize concentrating risks has lower (but safer) returns.

Derivatives Networks and Systemic Risk

- Financial innovations such as commodities futures and credit default swaps are intended to promote increased stability. Is this always true or can banks misuse these instruments?
  - Depends entirely on the multiplex network: the overlay of all networks, one for each related financial product.
  - Not sufficient to consider only one network in isolation. Completely misrepresentative of systemic risk.

- We analyze the CDS network overlaid with the unsecured debt network. Such a network exhibits robust-yet-fragile properties:
  - For the right CDS contract (between the right two parties) and for small liquidity shocks, contracts can reduce default cascades. Banks with excess liquidity can redistribute to those who desparately need repayments to stay solvent.
  - When liquidity shocks are large, or the CDS exposure is too great, contracts may do little to reduce a default cascade, while propagating distress to another part of the network.

- A key determinant of systemic risk in derivatives networks is wrong-way risk:
  - CDS network and debt network should not “look similar.” The banks in-distress during crisis should not be the same banks with potential CDS obligations.

Measuring Interconnectedness

- Clustering coefficient, eigenvector centrality, network density, etc. have been used to describe the interconnectivity of a network (Brunetti et al (2019)).
- What is the mechanism that makes "interconnectivity" transmit financial distress? Can we measure this directly?
  - How sensitive is bank j's borrowing to a liquidity shock at bank i?
- Use Fedwire data to monitor how the Fed funds lending network evolves over time (see Beltran et al (2015)). When liquidity risks increase for some banks in the network, how does this affect other institutions?
  - Inconclusive evidence on whether Lehman's collapse caused "contagion" as studied by many other papers (see survey Upper (2011)).
  - More important were fears of future liquidity problems that induced credit freezes ex-ante. Short-term funding markets were essentially non-existent in the wake of Lehman's default.
- Proposed Idea: Learning (Bayesian) graphical models.
  - Relationship between link $(i \to j)$ of Fed funds lending may depend on $(j \to k)$ or $(k \to \ell)$, but don't know.
  - Identify precisely how liquidity shocks spread to map how bank i's distress affects all other banks j in the network.

Interconnectivity Example

A Simple Model of Interconnectivity

- 3 red banks and 3 blue banks. Blue banks have access to unlimited funding at interest rate r_0, and red banks have unit-demand projects with return $r^* > r_0$.
  - Blue banks are liquidity providers and red banks are liquidity needers.

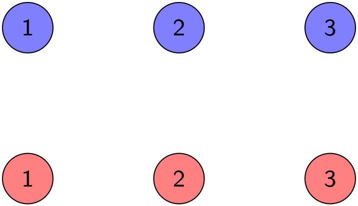
- Each red bank receives a liquidity shock and defaults with probability p, independently across banks. If the red bank defaults, it repays nothing.

- Each blue bank has a liquidity buffer of $\phi \in (0, 1)$ which measures how much of a loss the bank can absorb before it defaults on its own liabilities.

- Network formation process is exogenous, so we treat the network as given. Policymaker wants to study whether the current financial network is susceptible to **systemic troubles**.

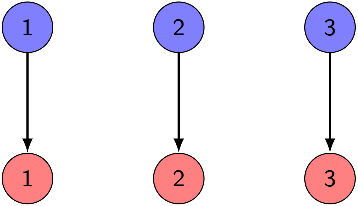
- When defaults are costly, is interconnectivity good or bad?

Option A: The Empty Network



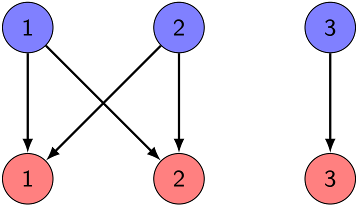
- Least susceptible to contagion because blue banks never default.
- Gains from trade are left untapped: unit-demand projects remain unfunded despite their return exceeding the cost of capital. If $r^* \gg r_0$, this is bad.

Option B: Segmented Lending



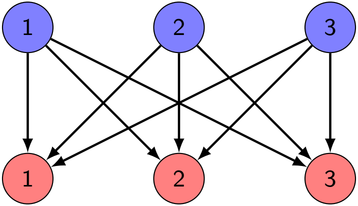
- All projects are funded, so gains from trade are maximized.
- Blue bank i defaults if and only if red bank i is hit with a liquidity shock.
- Every bank defaults with probability p, and there are no systemic defaults: each liquidity shock affects only a segmented part of the lending market.

Option C: Banks 1 and 2 Risk Share



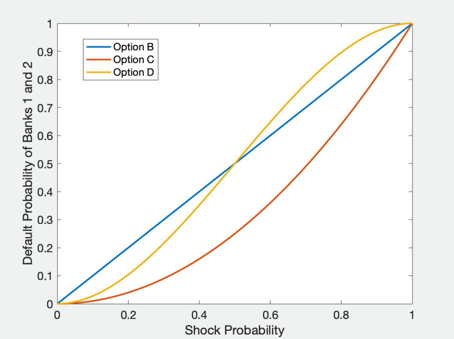
- Assume blue banks 1 and 2 risk share so they both lend 1/2 to red banks 1 and 2. Interconnectivity of the network has increased.
- When $\phi > 1/2$, blue banks 1 and 2 default if and only if both red banks 1 and 2 are hit with a liquidity shock. Blue bank 3 defaults if and only if red bank 3 is hit, the same as before.
- Strictly more stable than Option B: increased interconnectivity leads to a decrease in systemic risk. Gains from trade remain the same.
- The default is somewhat **systemic**, however, because either both banks 1 and 2 default or neither do.

Option D: Complete Network



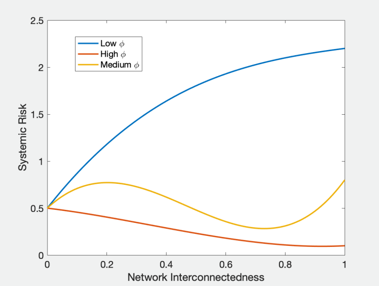
- Assume that $\phi \in (1/2, 2/3)$. Then increased interconnectivity from Option B to Option C reduced systemic risk.
- Suppose we continue to increase interconnectivity, so the network is now complete (each blue bank lends 1/3 to every red bank). Does systemic risk continue to decrease?
- The network is robust-yet-fragile: every blue bank defaults if and only if at least two red banks are hit with a shock, otherwise no blue bank defaults.
- Only (strictly) more stable than Option C if bank 3 (and only bank 3) defaults. Which network is more stable in expectation?

Option D, cont.



- Probability that bank 1 and bank 2 default is higher under Option D than Option C.
- If $p > 1/2$, then the probability any banks default is also higher under Option D than either Option B or C.
- The increase in interconnectivity makes the network very fragile.

General Trend



- When resilience is low (i.e., small ϕ) interconnectivity always increases systemic risk because shocks propagate.
- When resilience is high (i.e., large ϕ) interconnectivity always reduces systemic risk because shocks are well-absorbed by the system.
- When resilience is intermediate, non-monotone relationship between systemic risk and interconnectedness:
  - The empty network is always stable, but inefficient (option A).
  - A slightly connected network will be more susceptible to contagion (option B).
  - To a point, additional connections increase the stability of the system (option C).
  - Eventually, additional connections serve more to propagate shocks, and so systemic risk increases again (option D).

Roadmap

Why consider network dynamics?

- Many papers study contagion in financial networks: Acemoglu et al (2015), Cabrales et al (2015), Elliott et al (2014), Gai and Kapadia (2010), Jorian and Zhang (2009), Allen and Gale (2000).
  - Policy interventions are complex, highly sensitive to the network, computationally hard, and model-dependent.
- There are two other big challenges with network-based regulations:
  - Policymakers may observe only noisy snapshots of the financial network (see Ramirez (2019)), so policy may overfit to the observed network.
  - Regulatory policy enacted today can only protect against future crises, where the network may look different.
- Two channels for regulatory policy: preventative and protective.
  - Preventative policy changes how the network evolves by creating incentives for diversification and less concentrated risks.
  - Protective policy forces banks to take precautions in the event of a crisis.

Toy Policy Example

Dynamic Network Formation

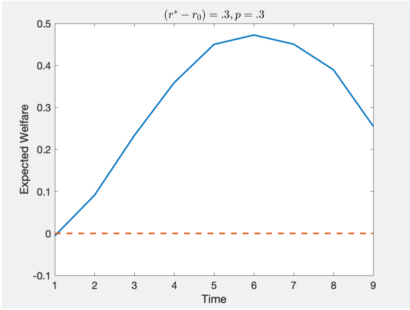
- Suppose time is discrete $t = 0, 1, 2, \ldots$ and at $t = 0$ the financial network is empty.
- In each time period, of the links missing between red and blue banks, one is added uniformly at random.
- In an ideal world, the policymaker could implement regulation that would force the network to not become any more "interconnected" (i.e., freeze the network structure).
- The crisis will come at time T, and the liquidity shocks will be realized. Welfare is measured at time T and is given by:

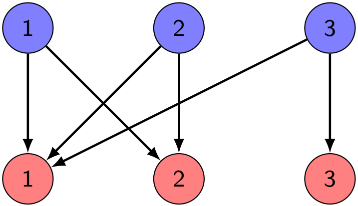
$$\text{welfare} = (r^* - r_0) \times (\text{number of projects funded}) - (\text{number of defaults})$$

- What is the optimal policy in this setting?

Simulated Welfare

- The policymaker solves a optimal stopping problem more generally.
  - When policymaker cannot observe network evolution, simply calculate expected welfare at time t, $\mathbb{E}W_t$, and solve $\arg\max_{t \leq T} \mathbb{E}W_t$.
  - When policymaker *can* observe network evolution, must solve full state-space DP model (does not scale well).





Robust Regulation on Dynamic Networks

Drawbacks to Exogenous Network Evolution

1. Banks form links in the network strategically over time. The exact law of motion for these links is crucial to understanding policy. What are the appropriate dynamics?
   - Link formation by probability matrix (Erdos-Renyi (1959))
   - Preferential attachment (Yule (1925))
   - Configuration model (Barabasi (1999))
   - Power-law models (most famously Chung-Lu (2002))

2. How do we expect policy to change the way the network evolves?
   - Previous example assumed some "magical" policy that discourages increasing interconnectedness. What is this in practice?
   - How do bank-level regulations change incentives and network formation?

An Elementary Model of Network Formation

- An economy $\mathcal{E}$ consists of n banks, each of which has its own balance sheet given by:

Assets	Liabilities
Cash (α_i)	Senior Debt (δ_i)
Other Assets (r_i)	Equity (s_i)
Shares $(\omega_{ij} s_j)$	

- Treat $\delta_i = \delta$ as given and constant, but the bank may choose in each period how much cash to hold $(\alpha_{i,t})$ and how much to invest in other banks' portfolios $(\omega_{ij,t})$.
- Each bank's assets have a value according to a log-normal distribution $\log(r_{i,t}) \sim \mathcal{N}(\mu_{i,t}, \sigma^2)$ with idiosyncratic mean but common variance.
- Each bank's equity is given by the accounting identity:

$$s_{i,t} = \alpha_{i,t} + r_{i,t} - \delta + (1 - \alpha_{i,t}) \sum_{j=1}^{n} \omega_{ij,t} s_{j,t}$$

with $\sum_{j=1}^{n} \omega_{ij,t} = 1$ for all t.

Information and Payoffs

- Banks are required to hold $\underline{\alpha}$ in cash, which for now is taken as exogenous.
- Each of the mean asset returns are initially set to $\mu_{i,0} = 0$. These evolve through time as an AR(1) process $\mu_{i,t} = \rho\mu_{i,t-1} + \kappa_{i,t}$ with $\kappa_{i,t} \sim \mathcal{N}(0, \sigma_\kappa^2)$, independent across banks and time.
- Banks receive private information about the true mean of the assets. In every period, bank i gets a signal (or message) $m_{ij,t}$ about bank j according to:

$$m_{ij,t} = \phi\mu_{j,t} + (1-\phi)\varepsilon_{j,t}$$

  where $\varepsilon_{j,t} \sim \mathcal{N}(0, \sigma_\varepsilon^2)$ (independent) and $\phi \in (0,1)$ is an exogenous parameter.
- Banks do not observe the financial decisions of other banks in the network.
- Banks are myopic and solve:

$$\max_{\alpha_{i,t},\omega_{ij,t}} \mathbb{E}\left[(s_{i,t})_+\right]$$

Characterization of Equilibrium

- Let $\mathbf{m}_{ij,t}$ denote the vector of all messages about bank j to bank i up until time t.

Theorem

There exists a pure strategy equilibrium of the following form: Each bank i uses the Kalman estimator function $\mathcal{K} : \mathbf{m}_{ij,t} \mapsto S_{ij,t}$ to obtain a Kalman score $S_{ij,t}$ for every other bank j. Then, for all banks i and bank $j^* = \max_k S_{ik,t}$, there exists $\underline{S}_t$ such that:

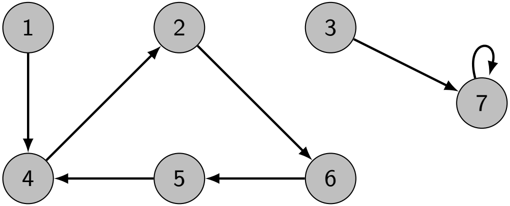
(a) *If $S_{ij^*,t} \geq \underline{S}_t$, $\alpha_{i,t} = \underline{\alpha}$ and $\omega_{ij^*,t} = 1$,*

(b) *otherwise, $\alpha_{i,t} = 1$.*

- This Kalman function computes $\mathbb{E}[\mu_{i,t}|\mathbf{m}_{ij,t}]$ by applying the Kalman filter techniques recursively.
  - The Kalman function can be expressed as just a function of today's observation $m_{ij,t}$ and yesterday's Kalman score $S_{ij,t-1}$.
  - For example, the Kalman function at $t = 1$ would be $\phi m_{ij,1} \propto m_{ij,1}$.
- Each bank invests entirely into the ex-ante most profitable bank; in other words, the bank with the largest $\mathbb{E}[\mu_{i,t}|\mathbf{m}_{ij,t}]$ (i.e., Kalman score).

Structure of Financial Network

- Financial network therefore always looks like a random 1-outdegree-regular network:[1]



- The exposure network consists of link $i \to j$ if and only if there exists a directed path from i to j in the financial network:
  - Bank 1 only holds shares of bank 4, but bank 4 is exposed to bank 2 as well. Bank 1 is indirectly exposed to bank 2's asset.
  - Bank 1 is exposed to banks 2, 4, 5, and 6, but no banks (other than 1) exposed to bank 1's project.

[1] Conditional on Kalman scores not being "too low." This is satisfied with high probability when the number of banks is large, for instance.

Steady-State Dynamics

- When $|\rho| < 1$, the AR(1) process for each project's expected return is stationary and the network dynamics are ergodic.
- Suppose we consider a snapshot of the network at some $T \gg 0$ for an ergodic network process. What is the distribution over financial networks?
  - Draw (expected) project returns according to $\mu_{i,T} \sim \mathcal{N}(0, \sigma_\mu^2)$, where $\sigma_\mu^2 = \sigma_\kappa^2/(1-\rho^2)$.
  - Using the asymptotics on the Kalman filter, we derive a closed-form for the distribution of $(S_{ij,T} - \mu_{j,T}) \sim \mathcal{N}(0, \sigma_T^2)$, where σ_T^2 is the unique solution to:

$$\begin{cases} \sigma_T^2 & = (1 - x\phi)y \\ x & = \frac{y\phi}{\phi^2 y + (1-\phi)^2 \sigma_\kappa^2} \\ y & = \rho^2 \sigma_T^2 + \sigma_\varepsilon^2 \end{cases}$$

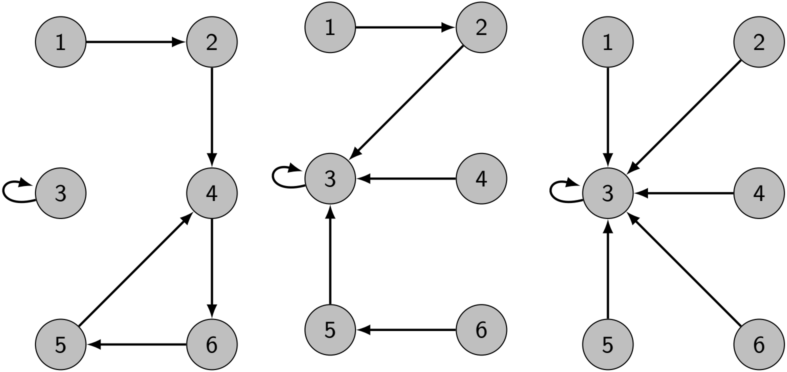
  - Want instead $S_{ij,T} | \mu_{j,T} \sim \mathcal{N}(\beta \mu_{j,T}, \sigma_S^2)$. Exact expressions for $\beta \in (0,1)$ and σ_S^2, but not clean.
- Each bank i connects to bank $j = \arg\max_k S_{ik,T}$ (conditional on $\max_k S_{ik,T} \geq \underline{S}$).
- Network structure depends entirely on the ratio between σ_μ^2 and $(\sigma_S/\beta)^2$!

Endogenous Financial Networks

Poisson
$(\sigma_S/\beta)^2 \gg \sigma_\mu^2$:

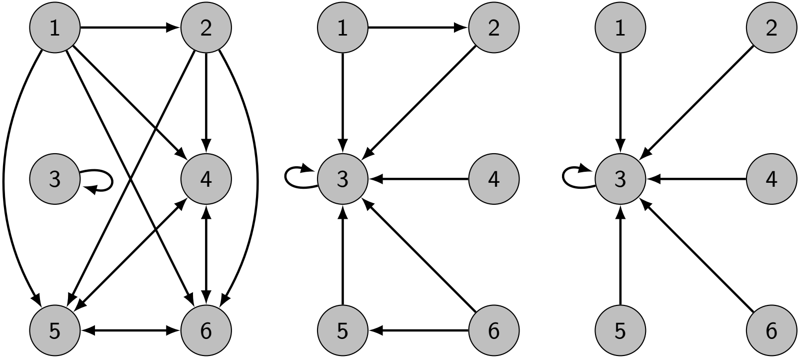
$(\sigma_S/\beta)^2 \propto \sigma_\mu^2$:

Preferential Attachment
$(\sigma_S/\beta)^2 \ll \sigma_\mu^2$:



Endogenous Exposures

$(\sigma_S/\beta)^2 \gg \sigma_\mu^2$: $(\sigma_S/\beta)^2 \propto \sigma_\mu^2$: $(\sigma_S/\beta)^2 \ll \sigma_\mu^2$:



Policymaker's Problem

- At some (random) time T crisis hits, and (fundamental) asset returns $\log(r_{i,T})$ are realized for every bank according to the distribution $\mathcal{N}(\mu_{i,T}, \sigma^2)$.
- Assume defaults are costly; that is, real value θ is is lost when a bank defaults on its loans.
- Debt holders of bank i receive δ when $s_{i,T} \geq 0$ and $\delta - |s_{i,T}| - \theta$ whenever $s_{i,T} < 0$. Banks issue repayments on debts they can make, d_i.
- Policymaker wishes to maximize the sum of equity and debt repayments $\mathbb{E}\left[\sum_{i=1}^{n}(s_{i,T} + d_i)\right]$. Basic tradeoff:
    - Because defaults are costly, wants to minimize similar exposures across banks, which lead to systemic failures. Prefers banks to be diversified.
    - Diversification implies investing in ex-ante less profitable projects, reducing bank equity.

Protective Policy

- Let $\boldsymbol{\Omega}$ denote the (adjacency) matrix of shares:

$$\boldsymbol{\Omega} = \begin{pmatrix} \omega_{11} & \omega_{12} & \cdots & \omega_{1n} \\ \omega_{21} & \omega_{22} & \cdots & \omega_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ \omega_{n1} & \omega_{n2} & \cdots & \omega_{nn} \end{pmatrix}$$

- Then, we can characterize the value of equity in closed-form:

$$\mathbf{s}_T = (\mathbf{I} - (\mathbf{1} - \boldsymbol{\alpha})\boldsymbol{\Omega}_T)^{-1}(\boldsymbol{\alpha} + \mathbf{r}_T - \boldsymbol{\delta})$$

- Note that $\boldsymbol{\alpha} = \mathbf{1}\underline{\alpha}$, and $\frac{\partial^2 s_{i,T}}{\partial r_{j,T} \partial \underline{\alpha}} < 0$ for all Ω_T, so the value of equity is less sensitive to individual asset returns when $\underline{\alpha}$ is larger.

- Also, increasing the value of $\underline{\alpha}$ does not affect the network evolution because it impacts all banks equally.

- Such a policy is protective, as it decreases defaults during a crisis (which also decreases equity values), but does not affect network formation.

Preventative Policy

- Suppose policymaker can regulate by setting heterogenous $\underline{\alpha}$ across banks.

- If policymaker does so for some set of (known) banks, expected equity returns of heavily regulated banks decline.
  - Only exacerbates the concentrated risk problem, as regulated banks will have rare connections.
  - Connections form to regulated banks only when Kalman score is *much* larger for these banks than other banks.

- What if the regulator imposes heterogenous regulations, but does so for highly-connected institutions?
  - Decreases effective $\mu_{i,t}$, but then all banks stack risk at the next highest Kalman score.
  - Set capital requirements according to a smooth policy function which moves with the bank's Kalman score.
  - Such a policy (effectively) decreases ϕ, thereby increasing $(\sigma_S/\beta)^2$. Leads to more symmetric networks.

Going Forward

- Tighter characterization of the optimal policy in steady state as a function of primitives of the model, including comparative statics of interest.
  - For example: when is transparency good or bad for financial stability?

- Characterize rate of convergence to steady state from an arbitrary network.
  - Get an approximate picture of how the financial network will look sometime in the not-so-distant future.
  - If the network is known today, and the crisis is soon, how does the optimal policy change (both protective and preventative policies)?
  - What value does the policymaker have in acquiring network knowledge today if the crisis is coming soon?

Roadmap

Derivatives Networks and Systemic Risk

What are derivatives?

- Products whose value *derives* from the value of another product.
  - Commodity futures: payout in the future based on the future value of a commodity such as corn or wheat.
  - Mortgage-backed security: "Diversified" package of mortgage loans whose value depends on repayments by homeowners.
  - Call option: Payout when stock does well, but "fixed fee" when stock does poorly (protected downside risk).

- Why do these products exist? Financial stability...
  - Commodity futures protect farmers who might have a bad crop yield, or manufacturing plant who wants stable input prices.
  - MBS offers diversified risks at higher yields (mitigates "reaching for yield" incentives).
  - Call options limit downside risks of portfolios.

- When do forms of securitization help improve systemic risk?

Credit-Default Swaps

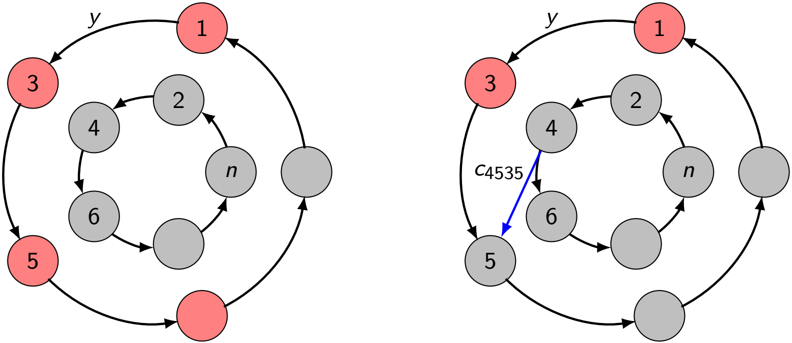
- For simplicity, let us consider the credit-default swap (CDS) market, but results can be generalized to (mostly) any type of securitized product.
  - Notional amount of CDS outstanding just prior to the crisis was over $40 trillion USD. While the size of the market declined in 2009-2011, today's CDS notional is estimated at over $48 trillion USD (see Aldasoro and Ehlers (2018)).
- Bank i sells a CDS to bank j on bank k. If bank k defaults on its debt, it is bank i's responsibility to pay bank j the difference between what bank k owes on its debt and how much bank k repaid.
  - In return, bank j pays a small premium (say, monthly) to bank i in order to have the insurance contract on bank k's debt.
- CDS contracts can limit or prevent default cascades, because it insulates banks from liquidity shocks.
  - But, can propagate shocks if short CDS contracts push an institution into default, like AIG.
  - How do these to effects compete?

A Basic Model of CDS Trading

- Take a simplified version of the model by Acemoglu et al (2015).
  - At time $t = 0$, take the network of debts as given. Bank j owes bank i, $x_{j \to i}$, at time $t = 1$.
  - At $t = 1$, before repayments are made, project returns are realized $z_i \in \{a, a - \varepsilon_i\}$. All banks have outside debt v which is senior to the debt given by $x_{j \to i}$.
  - For simplicity, assume except for bank 1, $\varepsilon_i = 0$, so banks $2, \ldots, n$ are safe with probability 1. On the other hand, $\varepsilon_1 > 0$, so bank 1 may be hit with a liquidity shock.
  - Repayments are given by $y_{j \to i} = \min\{x_{j \to i}, z_i - v + \sum_{k=1}^{n} y_{k \to j}\}$.

- Banks may also have outstanding CDS contracts at time $t = 0$, which payout the difference between x and y. Formally, a CDS contract $c_{ijk\ell} \in \{0, 1\}$ specifies four institutions:
  - Bank i, the bank short the CDS contract.
  - Bank j, the bank long the CDS contract.
  - Bank k, the bank whose default triggers the CDS.
  - Bank ℓ, the bank who should receive payment from bank k. This determines the payoff of the CDS contract, which is equal to $x_{k \to \ell} - y_{k \to \ell}$.

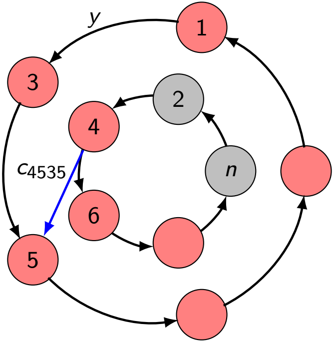
An Example of Stability with Small Shocks



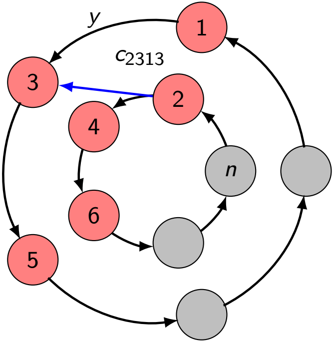
(a) Without CDS (b) With CDS

- Small shocks leads to a cascade of defaults in the larger ring. Inner ring is unaffected.
- CDS contract can be used to redistribute excess liquidity of inner circle to outer circle without triggering financial distress in the inner circle.

Examples of Instability



(c) Big Shock

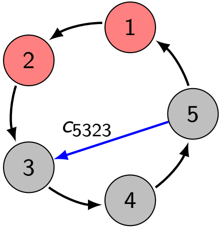


(d) Big Defaults

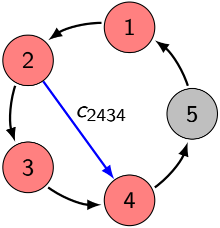
- CDS protection is robust-yet-fragile: when a big shock comes, it can wipe out the bank selling the CDS, triggering financial distress while doing little to alleviate the spread of the original liquidity shock.
- CDS contracts can slow the propagation of shocks in one part of the network, but introduce similar fragilities elsewhere. Systemic risks from additional interconnectedness may outweigh benefits.

Wrong-Way Risks and Networks

- Consider the multiplex network (i.e., overlapping layers of networks across the same set of financial institutions) which describes debt relationships, but also CDS contract relationships (of which there may be many).
  - Level of systemic risk involves the interaction between these networks. Not enough to consider each one in isolation.
- Wrong-way risk measures the level of "similarity" between these networks. This type of risk amplifies systemic problems because the banks required to payout on CDS contracts are exactly those institutions most in-distress when the crisis hits.



(e) "Right-Way" Risk



(f) Wrong-Way Risk

- How can we measure the similarity (or correlation) across networks in a multiplex setting to better understand interconnectedness?

Summary and Going Forward

- Financial derivatives can improve stability, but they can also exacerbate shocks and trigger systemic problems.

- Few papers consider the network interactions across different asset classes (e.g., Duffie (2011)), but when these assets interact in significant ways (as do derivatives by definition), picture of systemic risk depends on multiplex network.

- Does naked CDS (i.e., $c_{\cdot j \cdot \ell} = 1$ where $j \neq \ell$) ever create stability?
  - **Conjecture**: For every network where a naked CDS is traded, there exists another network with no naked CDS that is at least as systemically resilient.

- Can policy play a role in regulating CDS trades, to avoid "bad types" of interconnectedness (e.g., naked CDS)?
  - To what extent is wrong-way risk priced-in endogenously (see Du (2016))?
  - May need to consider endogenous CDS contract pricing in networks to understand the biggest fragilities.

Roadmap

Measuring Interconnectedness

Roadmap

Concluding Remarks

- What is the relationship between distress, regulation, interconnectedness, and systemic risk? Three key ideas we need to understand:
    1. How does regulation affect the resiliency of the network with uncertain dynamics (e.g., credit cycles)?
    2. When do complex financial products improve financial stability?
    3. How do we empirically measure interconnectedness and structure network-based regulatory policy?

- Answers to these questions are complex, but the problems themselves are complex.
    - Network theory offers a rich framework with new insights.
    - There needs to be an emphasis on simplicity in network analysis to distill the key mechanisms that link interconnectedness and systemic risk. Much more work to be done.