Research Statement

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Contents

Education Background

Education Background

- Bachelor of Economics in Lingnan College, Sun Yat-Sen University from Sep 2017 to Jun 2021,
- Master of Finance in Lingnan College, Sun Yat-Sen University from Sep 2021 to Jun 2023,
- PhD student of Finance in **Guanghua School of Management, Peking University** from Aug 2023 to present,
- Exchange in **Warwick Business School, University of Warwick** from Sep 2019 to Dec 2019.

Research Fields in Finance

Research Fields of interest in Finance

1. **Financial Network**
   - Financial Crisis and Financial Network Stability—Based on the perspective of risk contagion in the financial system.

2. **Financial Econometrics**
   - The impact of uncertainty shock to consumption under different confidence regimes—Based on stochastic-uncertainty-in-mean-TVAR model (submited to *Empirical Economics*),
   - The volatility of Shanghai Interbank Offered Rate—Based on ARFIMA-ARCH model.

3. **Finanical Economics**
   - **Optimal Coupon Cooperation policy of E-commerce Platforms and E-tailers and its benefit (published in *Systems Engineering – Theory & Practice*)**,
   - Does Technological Progress aggravate consumption inequality between urban sector and rural sector?—Based on the price effect and the common prosperity effect,
   - How does WHO warn the world? —Based on two-stage dynamic Bayesian persuasion game.

Working Papers

Financial Crisis and Financial Network Stability

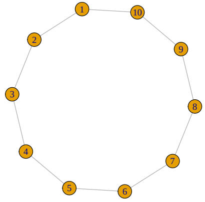
—Based on the perspective of risk contagion in the financial system

Motivation

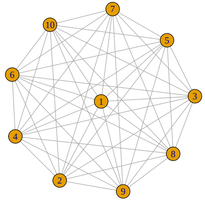
- Increasingly intricate interdependencies among financial institutions in different countries may increase the possibilities of financial tsunamis,
- Different structures of a financial network may affect the contagion of risks among its nodes (i.e. different financial institutes),
- Building on Acemoglu et al. (2015), I want to find out the consequences of different topologies of an exposure network for the impact of a particular institution's failure.

Systemic Risk and Networks

- A common hypothesis: more interbank connections enhance the resilience of the financial system to idiosyncratic shocks,whereas “sparser” network structures are more fragile.
  - Kiyotaki and Moore (2002),
  - Allen and Gale (2000),
  - Freixas et al. (2000).



- But also the opposite perspective: more densely connected financial networks are more prone to systemic risk: reminiscent of epidemics.
  - Blume et al. (2011).



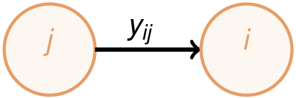
- In the context of input-output economies with linear interactions, sparsity is *not relevant*. Rather it is the symmetry that matters.
  - Acemoglu et al. (2012).

This paper

- A model of interbank lending and counterparty risk in financial networks.
- The form of interactions and magnitude of shocks are crucial for understanding systemic risk and fragility.
  - For **small shocks**, sparsity implies fragility and interconnectivity implies stability,
  - Phase Transition: with **large shocks**, the more complete networks become most fragile, whereas “weakly connected” networks become stable.

A Minimalist Model of Financial Networks

- n risk-neutral financial institutions (banks),
- three dates: $t = 0, 1, 2$,
- each bank has an initial capital k.
- Banks lend to one another at $t = 0$ and write standard debt contracts in exchange.
  - to be repaid at $t = 1$,
  - face values: $\{y_{ij}\}$: how much bank j owes bank i?
  - defines a financial network:



- Take the interbank commitments as given.

A Minimalist Model of Financial Networks

- After borrowing, bank i invests in a project with returns at $t = 1, 2$.
  - random return of z_i at $t = 1$.
  - deterministic return of A at $t = 2$ (if held to maturity)
- Bank i's obligations:
  - Interbank commitments $\{y_{ji}\}$,
  - A more senior outside obligation of value $\nu > 0$.
- If the bank cannot meet its obligations, it defaults:
  - liquidates its project prematurely and gets ζA,
  - costly liquidation: $\zeta < 1$,
  - pays back its creditors on *pro rata* basis.

Summary: Timing and Description of Events

- $t = 0$:
  - interbank lending happens,
  - banks invest in projects.
- $t = 1$:
  - short term returns $\{z_i\}$ are realized,
  - banks have to meet the interbank and outside obligations,
  - any shortfall leads to default and forces costly liquidation.
- $t = 2$:
  - remaining assets have their long-run returns realized.

Payment Equilibrium

- Focus on $t = 1$ with the financial network taken as given:
  - z_j: short-term returns,
  - c_j: cash,
  - y_j: total commitments(debt) of bank j to all other banks,
  - ℓ_j: liquidation amount,
  - ν: outside commitments.

- How much bank j will pay bank i at time $t = 1$?

$$x_{ij} = \begin{cases} y_{ij}, & \text{if } c_j + z_j + \ell_j + \sum_s x_{js} \geq \nu + y_j, \\ \frac{y_{ij}}{y_j}\left(c_j + z_j + \ell_j + \sum_s x_{js} - \nu\right), & \text{if } c_j + z_j + \ell_j + \sum_s x_{js} \in \left(\nu, \nu + y_j\right), \\ 0, & \text{if } c_j + z_j + \ell_j + \sum_s x_{js} \in (0, \nu). \end{cases}$$

Payment Equilibrium

- Let $Q = [y_{ij}/y_j]$ and $x_{ij} = q_{ij}x_j$,

$$\begin{aligned} x &= [\min\{Qx + c + z + \ell, y\}]^+, \\ \ell &= [\min\{y - (Qx + c + z), \zeta A\}]^+. \end{aligned}$$

- Payment equilibrium: a fixed point $\{x, \ell\}$ of the above set of equations.

Proposition

A payment equilibrium exists and is generically unique.

Notions of Fragility

- Focus on regular financial networks: $y_j = y$ for all j.

- Also assume
  - $\zeta = 0$
  - $z_j \in \{a, a - \epsilon\}$
  - $c_j = 0$

Lemma

Conditional on the realization of a shock, the social surplus in the economy is equal to

$$W = na - \epsilon + (n - \sharp \text{ defaults })A.$$

- Number of defaults in the presence of one negative shocks
  - Resilience: **maximum** possible number of defaults,
  - Stability: **expected** number of defaults

Small Shock Regime

Proposition

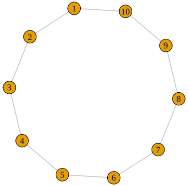
There exist ϵ^* and y^* such that for all $\epsilon < \epsilon^*$ and $y > y^*$,

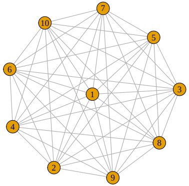
(a) *the complete financial network is the most stable and most resilient,*

(b) *the ring financial network is the least stable and resilient,*

(c) *the γ-convex combination of the ring and complete financial networks becomes more stable and resilient as γ increases.*

$$y_{ij} = (1-\gamma)y_{ij}^{\text{ring}} + \gamma y_{ij}^{\text{comp}}$$





Insights under Small Shock Regime

- Sparsity $\Rightarrow$ Fragility,
  Interconnectivity $\Rightarrow$ Resilience.

- Intuition: the complete network reduces the impact of a given bank's failure on any other bank, whereas in the ring, all the losses are transferred to the next bank.

δ-connected financial networks ▸ $\Rightarrow$

Definition

- Financial network is δ-connected if there exists a subset M such that
  (a) $y_{ij} \leq \delta$ for all $i \in M$ and $j \notin M$,
  (b) $y_{ij} \leq \delta$ for all $i \notin M$ and $j \in M$.

- Financial network disconnected if $\delta = 0$.

- "weakly connected" if δ is small

Large Shock Regime

Proposition

If $\epsilon > \epsilon^*$ and $y > y^*$, then

- complete and ring networks are the least resilient and stable networks,
- for δ small enough, δ-connected networks are more stable and resilient than both.

- Phase transition/Regime change:
  with large shocks, the complete is as fragile as the ring.

Insights under Larger Shock Regime

- Two absorption mechanisms:
  i The excess liquidity of non-distressed banks $a - \nu > 0$,
  ii The senior creditors of the distressed banks with claims ν.

- The complete network:
  - utilizes (i) very effectively, more than any other network,
  - utilizes (ii) less than any other network,
  - when shocks are small, (i) can absorb all the losses.

- Weakly connected networks:
  - do not utilize (i) that much,
  - utilize (ii) very effectively,
  - with *large shocks*, networks that utilize (ii) more effectively are more stable.

Harmonic Distance

- Normalize the interbank commitments: $q_{ji} = y_{ji}/y$,
- Harmonic distance: Suppose that bank i is hit with the shock:

$$m_{ji} = 1 + \sum_{k \neq j} q_{jk} m_{ki}$$

Proposition

Suppose that $\epsilon > \epsilon^*$ and let $m^* = y/(a - v)$.

(a) If $m_{ji} < m^*$, then bank j defaults.

(b) If all banks default, then $m_{ji} < m^*$ for all j.

Identifying SIFIs

- “More connectivity” (shorter distances) means more fragility.
- The closer other banks are to j, the more “systematically important” it is.
- Off-the-shelf measures of network centrality may not be the right notions for identifying SIFIs.

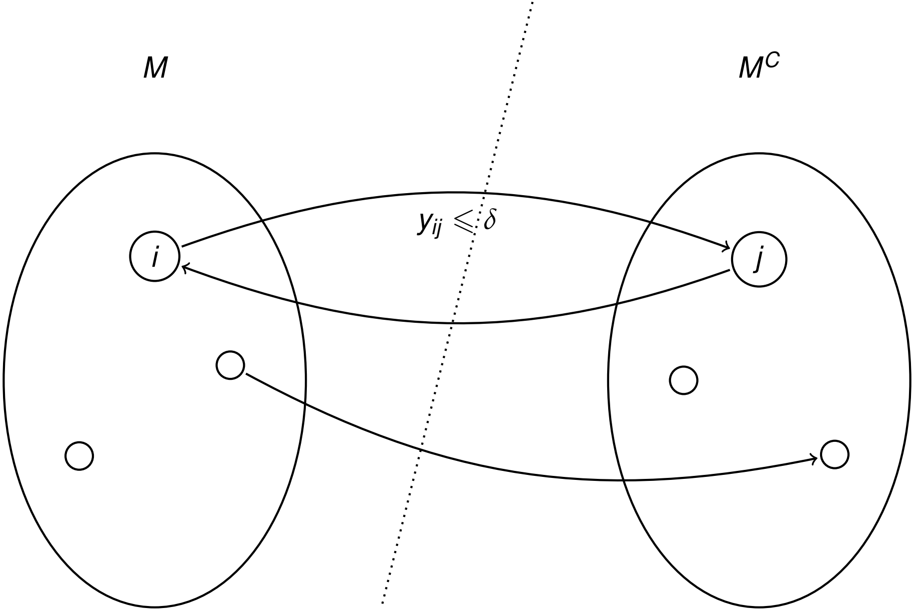
The Bottleneck Parameter

- Bottleneck Parameter:

$$\phi = \min_{M \subseteq N} \sum_{\substack{i \in M \\ j \notin M}} \frac{y_{ij}}{|M|\,|M^c|}$$

- How easy to “cut” the financial network into two components?
- Captures the extent of connectivity of the network.
- SEE THE NEXT SLIDE ! ⇒

δ-connected network ▸ ⇒



Large Shock Regime

Lemma

For any symmetric financial network,

$$\frac{1}{2n\phi} \leq \max_{i \neq j} m_{ij} \leq \frac{16}{n\phi^2}.$$

Corollary

Suppose that $\epsilon > \epsilon^*$. Then there exists constants $\bar{\phi} > \underline{\phi}$ such that

(a) *if $\phi > \bar{\phi}$, then all banks default;*

(b) *if $\phi < \underline{\phi}$, then at least one bank does not default.*

More interconnectivity implies more fragility.

Robust-Yet-Fragile Financial Networks

- Interconnected financial network are simultaneously
  - very robust to small shocks,
  - very fragile in the face of large shocks.

Summary

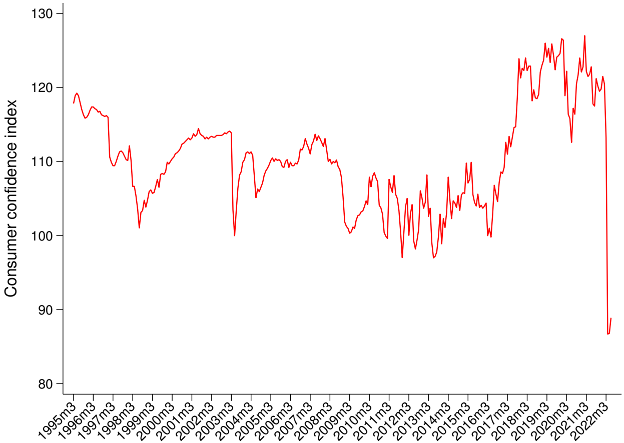
- A framework for studying the relationship between the structure of financial networks and the extent of contagion and cascading failures
- Small shocks: rings are most unstable and the complete network is the most stable
- For large shocks, there is a phase transition: complete network is the most unstable, and strictly less stable than weakly connected networks.

The impact of uncertainty shock to consumption under different confidence regimes

—Based on stochastic-uncertainty-in-mean-TVAR model

Motivation

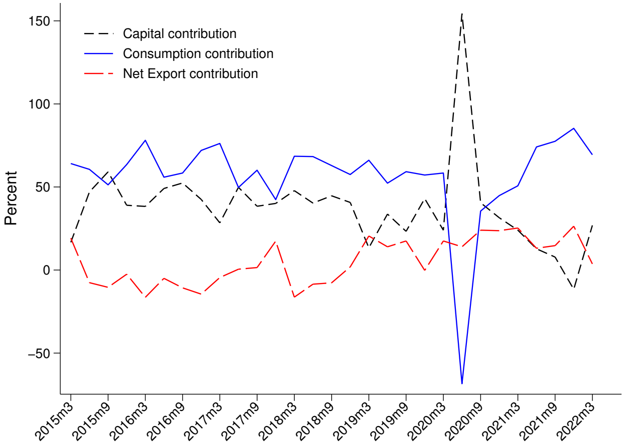
- Volatile Chinese consumer confidence (CCI), $\Rightarrow$



Motivation

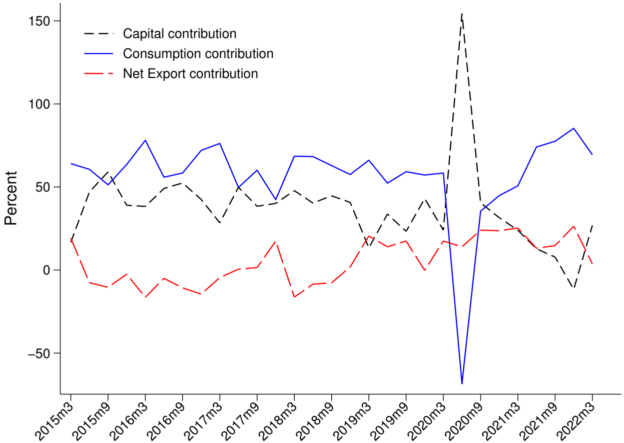
- Volatile Chinese consumer confidence (CCI), $\Rightarrow$

- Consumption contributes the most to Chinese economy among "three carriages", $\Rightarrow$



Motivation

- Volatile Chinese consumer confidence (CCI), $\Rightarrow$
- Consumption contributes the most to Chinese economy among "three carriages", $\Rightarrow$
- Will the exogenous shock cause different effects on the Chinese economy, especially consumption, under different CCI regimes?



Contributions I

- Allows the stochastic uncertainty to affect simultaneously:
  - ✓ the endogenous variables directly in the mean equation [First order moment],
  - ✓ the covariance matrix of the disturbance term in the mean equation [Second order moment].

$$
\begin{aligned}
Z_t = &\left(c_1 + \sum_{j=1}^{M} \beta_{1j} Z_{t-j} + \sum_{j=0}^{J} \gamma_{1j} \ln \lambda_{t-j} + \Omega_{1t}^{1/2} e_t \right) \tilde{S}_t \\
&+ \left(c_2 + \sum_{j=1}^{M} \beta_{2j} Z_{t-j} + \sum_{j=0}^{J} \gamma_{2j} \ln \lambda_{t-j} + \Omega_{2t}^{1/2} e_t \right) \left(1 - \tilde{S}_t\right)
\end{aligned} \tag{1}
$$

where

$$
\begin{aligned}
\Omega_{1t} &= A_1^{-1} H_t A_1^{-1'} \\
\Omega_{2t} &= A_2^{-1} H_t A_2^{-1'} \\
H_t &= \lambda_t S \\
\ln \lambda_t &= \alpha + F \ln \lambda_{t-1} + \eta_t
\end{aligned} \tag{2}
$$

Contributions II

- Considers the threshold effect of endogenous consumer confidence to capture the impact of uncertainty shocks on macroeconomic variables under different consumer confidence regimes.

$$
\begin{aligned}
Z_t = & \left(c_1 + \sum_{j=1}^{M} \beta_{1j} Z_{t-j} + \sum_{j=0}^{J} \gamma_{1j} \ln \lambda_{t-j} + \Omega_{1t}^{1/2} e_t \right) \tilde{S}_t \\
& + \left(c_2 + \sum_{j=1}^{M} \beta_{2j} Z_{t-j} + \sum_{j=0}^{J} \gamma_{2j} \ln \lambda_{t-j} + \Omega_{2t}^{1/2} e_t \right) \left(1 - \tilde{S}_t\right)
\end{aligned}
\tag{3}
$$

where

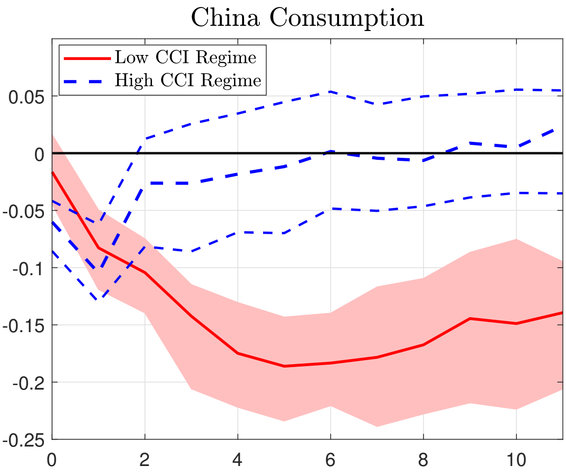
$$
\tilde{S}_t = 1 \left\{ CCI_{t-d} \leq Z^* \right\}
$$

Results I

- In China, compared to high CCI, low CCI will

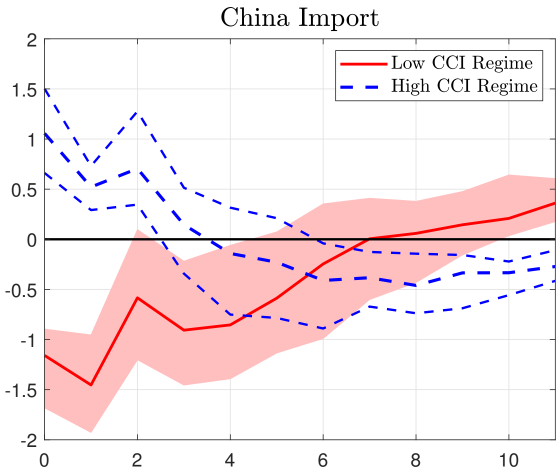
Results I

- In China, compared to high CCI, low CCI will
  - exacerbate domestic consumption,



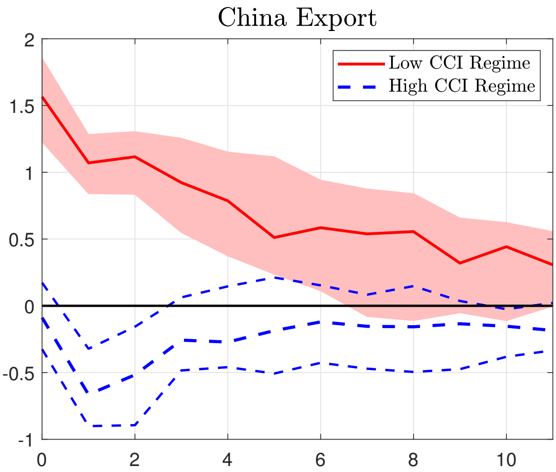
Results I

- In China, compared to high CCI, low CCI will
  - exacerbate domestic consumption,
  - deteriorate import,



Results I

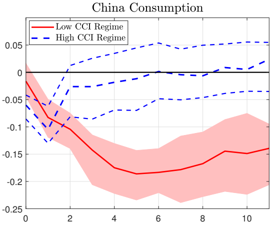
- In China, compared to high CCI, low CCI will
  - exacerbate domestic consumption,
  - deteriorate import,
  - benefit export.

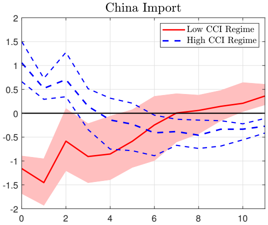


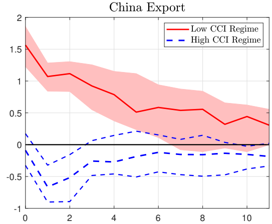
Results I

- In China, compared to high CCI, low CCI will
  - exacerbate domestic consumption,
  - deteriorate import,
  - benefit export.

- Low CCI regime means domestic consumers are more pessimistic than foreign consumers,
  - they would purchase less from both *home* (domestic consumption) and *abroad* (import),
  - *foreign* consumers will buy more (export).

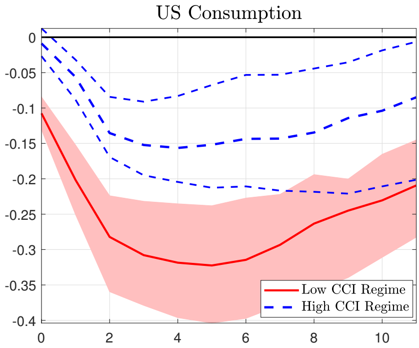


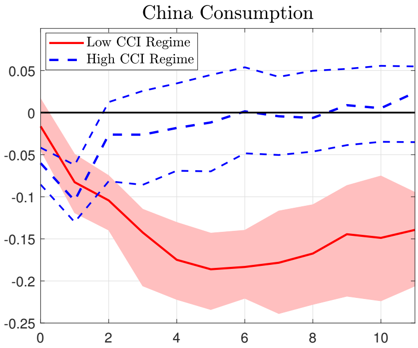




Results II

- Consumer confidence is much more influential in US than China.





Optimal Coupon Cooperation policy of E-commerce Platforms and E-tailers and its benefit

Yan Zeng, Xuefeng Wu, Junqing Kang, Zhuoran Chen

(Lingnan College, Sun Yat-sen University; Imperial College Business School)

Motivation

- Issuing consumption coupons cooperatively by e-commerce platforms and their merchants is recently an innovative and promising trend in platform economy.
- Several typical examples:
  - ”Ten Billion Yuan subsidy program” by Pinduoduo since June, 2019;
  - ”Juhuasuan subsidy program (USD 1.4 billion)” by Alibaba since Dec, 2019;
  - AliExpress claims to subsidize retailers $3/order since March 2020.
  - ...

Relevant Questions

- How to maximize the profits of both e-commerce platform and its merchants while protecting consumers' legal rights at the same time?
  - ✓ Are the merchants willing to participate in the program, and if not, how to beef up their enthusiasm?
  - ✓ What are the effects of cooperate coupon issuing on the advertising inputs of the merchants?
  - ✓ Will cooperative coupon issuing benefit consumers (the prices of the commodities)?

Results I

Q1 Are the merchants willing to participate in the program, and if not, how to beef up their enthusiasm?

A1 Merchants' willingness to engage will increase if

- the platform commissions decrease,
- the market scale of merchants' platform sales channel increases,
- the advertisements input of e-commerce platform increases.

Results II

Q2 What are the effects of cooperate coupon issuing affect the advertising input of the merchants?

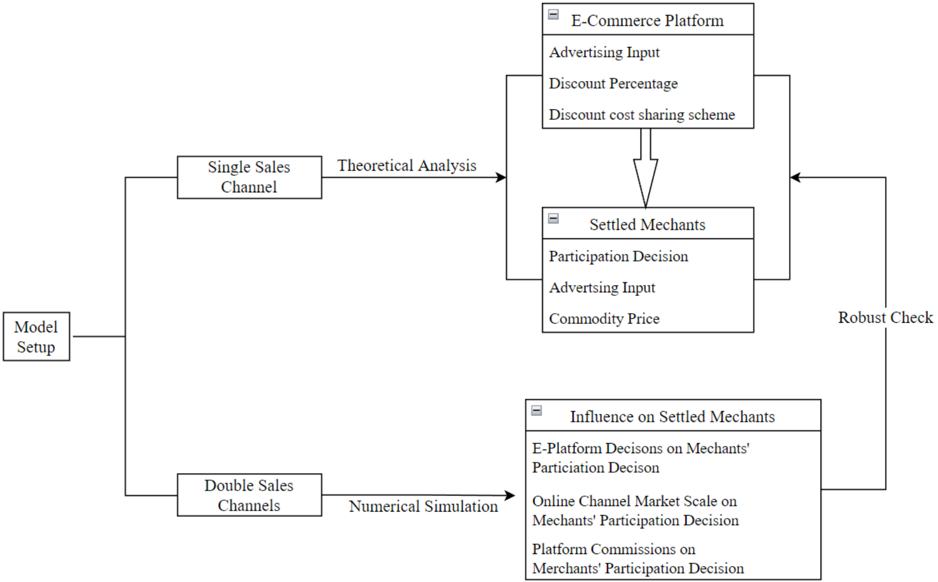
A2 There is a positive correlation between participation decision and advertisements input.

Results III

Q3 Will cooperative coupon issuing benefit consumers (the prices of the commodities)?

A3 The actual price facing consumers goes up due to cooperative coupon issuing if merchants can rely more on commercials to increase the demands.

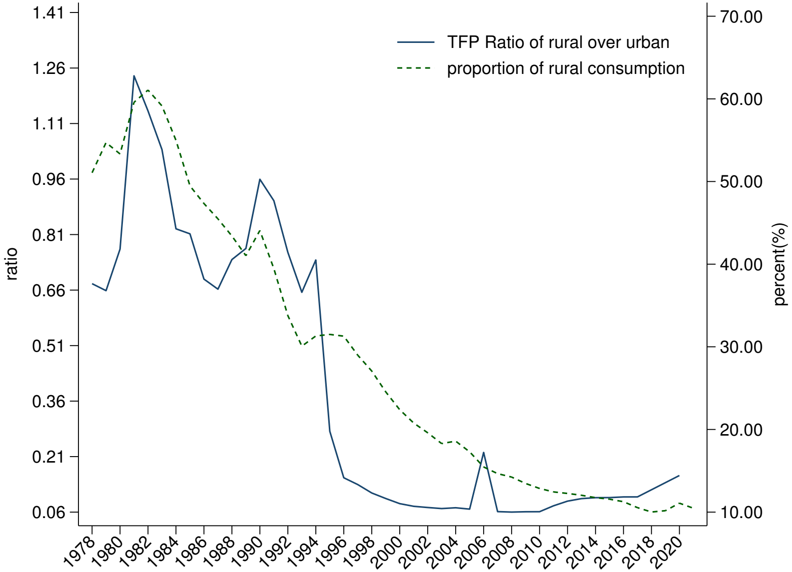
Framework


E-Commerce Platform
Advertising Input
Discount Percentage
Discount cost sharing scheme
Settled Mechants
Participation Decision
Advertsing Input
Commodity Price
Single Sales Channel
Theoretical Analysis
Model Setup
Robust Check
Influence on Settled Mechants
E-Platform Decisons on Mechants' Particiation Decison
Online Channel Market Scale on Mechants' Participation Decision
Platform Commissions on Merchants' Participation Decision
Double Sales Channels
Numerical Simulation

Does Technological Progress aggravate consumption inequality between urban sector and rural sector

—Based on the price effect and the common prosperity effect

Motivation



TFP Ratio of rural over urban
proportion of rural consumption
ratio
percent(%)
1.41
1.26
1.11
0.96
0.81
0.66
0.51
0.36
0.21
0.06
70.00
60.00
50.00
40.00
30.00
20.00
10.00
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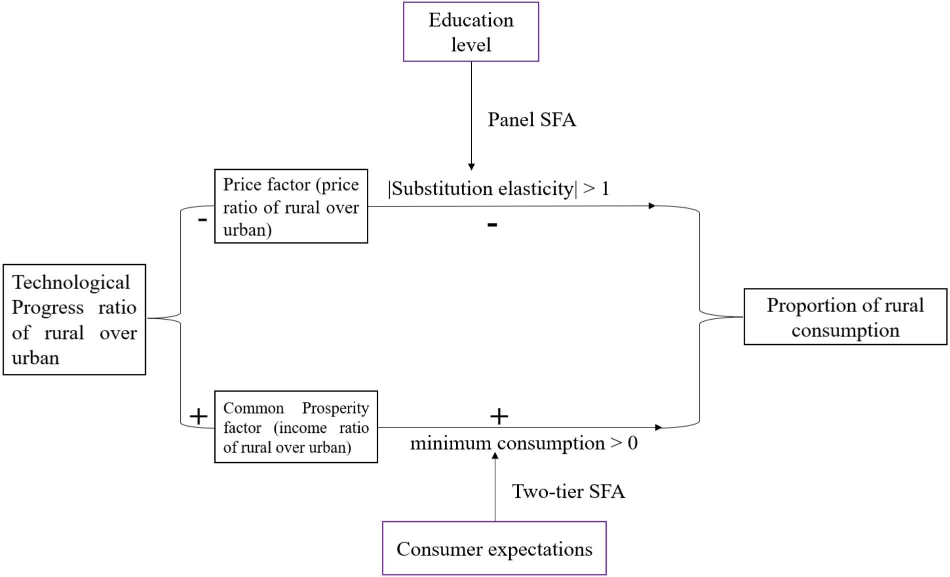
Framework ▸ PriceEffect ▸ Next



Price Effect

-
$$\frac{P_1 c_1}{P_2 c_2} = \frac{\omega_1}{\omega_2} \left(\frac{P_1}{P_2} \right)^{1-\epsilon} \tag{4}$$

  - With low substitution elasticity ($\epsilon < 1$), the increase of price ratio (rural over urban) will increase the proportion of rural consumption,
  - With high substitution elasticity ($\epsilon > 1$), the increase of price ratio (rural over urban) will decrease the proportion of rural consumption.

- Since
$$\frac{P_1}{P_2} = \frac{w_1 A_2}{w_2 A_1} \tag{5}$$

- Urban sector with faster tech progress will bring the decrease of its relative price, thus increasing its consumption proportion given high substitution elasticity in China.

Common Prosperity Effect ‣ Back

- Since

$$\frac{P_1}{P_2} = \frac{w_1 A_2}{w_2 A_1} = \xi \frac{A_2}{A_1}$$

- Proportion of rural consumption x_1^c

$$x_1^c = \frac{P_1 c_1}{P_2 c_2 + P_1 c_1} = \frac{\xi x_1^l}{x_2^l + \xi x_1^l} \propto \xi x_1^l \tag{6}$$

$$\xi x_1^l = \frac{\xi \omega_1 A_2^{1-\epsilon}}{\omega_1 A_2^{1-\epsilon} + \xi^{\epsilon} \omega_2 A_1^{1-\epsilon}} - \frac{\xi^{\epsilon+1} \omega_2 A_1^{1-\epsilon}}{\omega_1 A_2^{1-\epsilon} + \xi^{\epsilon} \omega_2 A_1^{1-\epsilon}} \frac{\overline{c_1}}{A_1 L} \tag{7}$$

- It turns out that if $\bar{c}_1 < 0$ and $\xi \in (0, 1)$, ξx_1^l will decrease with the decline of ξ.

- Enlarging of income gap between urban and rural sectors may shrink the proportion of rural consumption.

How does WHO warn the world?

—Based on two-stage dynamic Bayesian persuasion game

Motivation

- Builds on Alizamir et al. (2020), I construct a dynamic Bayesian persuasion game model about how an informed agency will warn an uninformed stakeholders to take preemptive actions after the agency receives early information and apply this model to explain why WHO was criticized “*bungling the response and failing to communicate the disease’s threat*” during 2020.

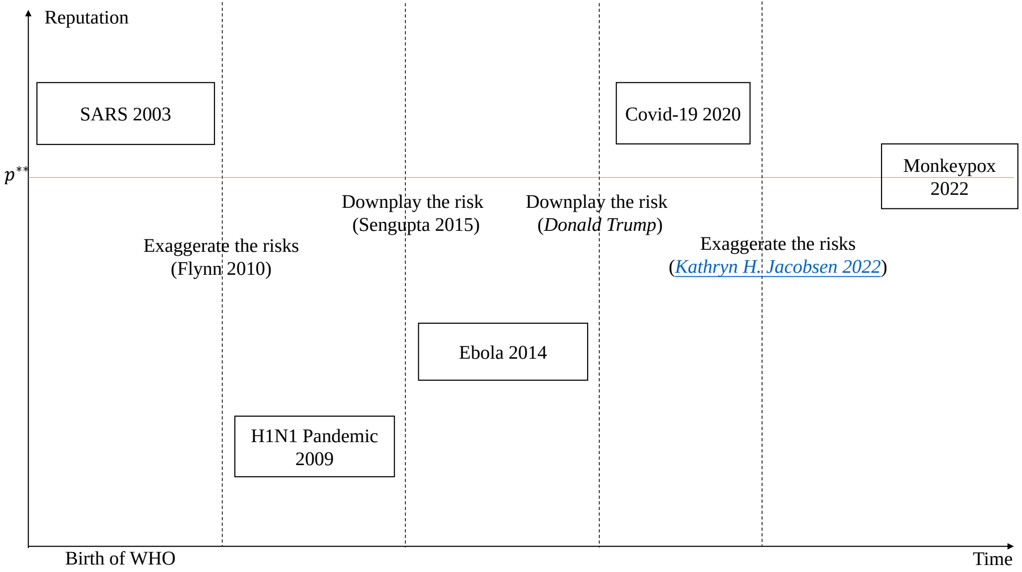
The game

- The agency privately receives early information about recurring harmful events and issues warnings to induce an uninformed stakeholder to take preemptive actions.
- The agency's decision to issue a warning critically depends on its reputation: the stakeholder's belief regarding the accuracy of the agency's information.
- The agency faces a trade-off between eliciting a proper response today and maintaining its reputation to elicit responses to future events.

Results

- The efficacy of the warning hinges on the credibility of the agency, or the agency's reputation.
  - low: downplay the risk to restore its reputation in the future,
  - high: exaggerate the risk to reduce the loss in its credibility.

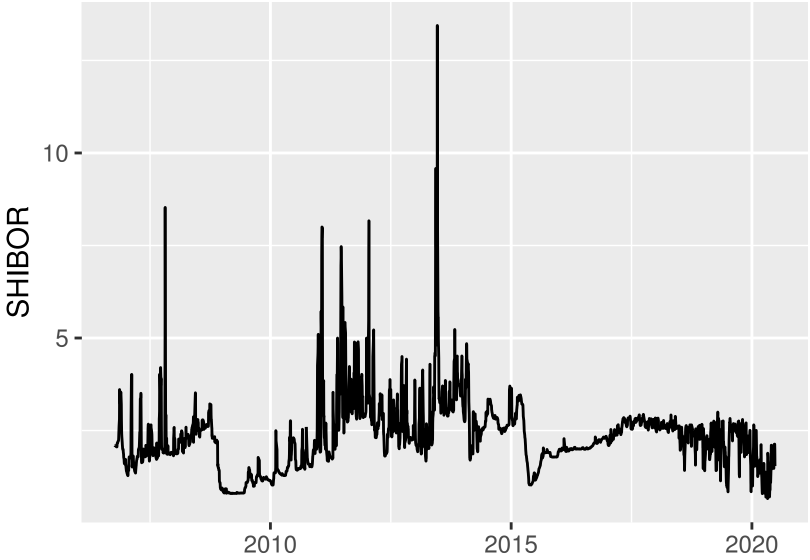
Insights



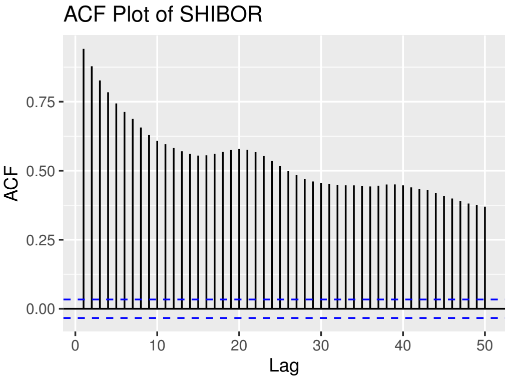
Reputation
SARS 2003
Covid-19 2020
p^{**}
Monkeypox 2022
Downplay the risk (Sengupta 2015)
Downplay the risk (*Donald Trump*)
Exaggerate the risks (Flynn 2010)
Exaggerate the risks (*Kathryn H. Jacobsen 2022*)
Ebola 2014
H1N1 Pandemic 2009
Birth of WHO
Time

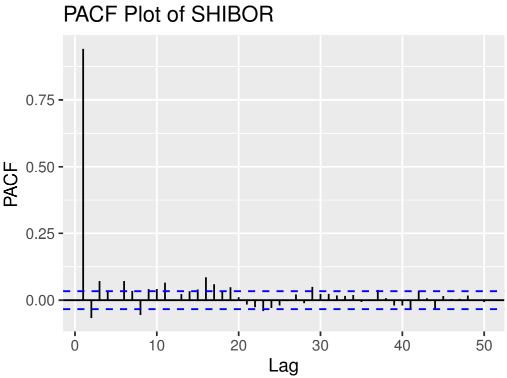
The volatility of Shanghai Interbank Offered Rate—Based on ARFIMA-ARCH model.

SHIBOR from 2006 to 2020



ACF & PACF Plot of SHIBOR from 2006 to 2020





$ARFIMA(p, d, q)$ model

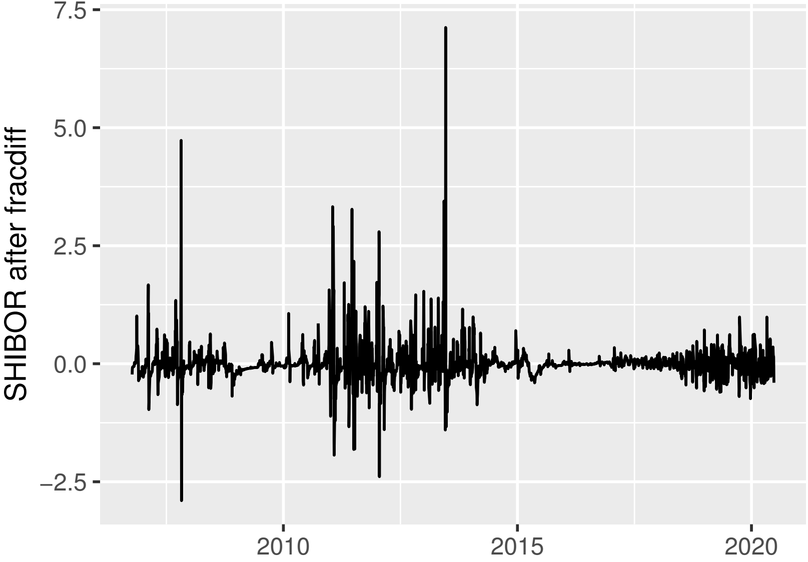
- $ARFIMA(p, d, q)$ model is

$$\psi(L)(1-L)^d\,(y_t-\mu)=\theta(L)\varepsilon_t$$

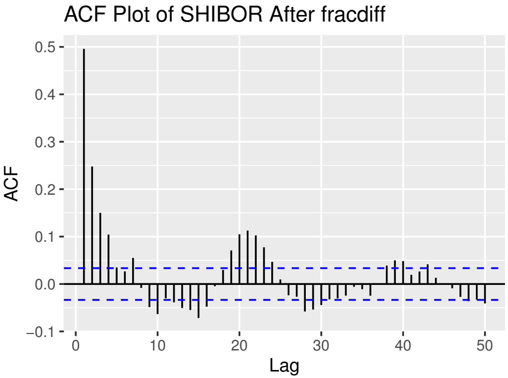
where

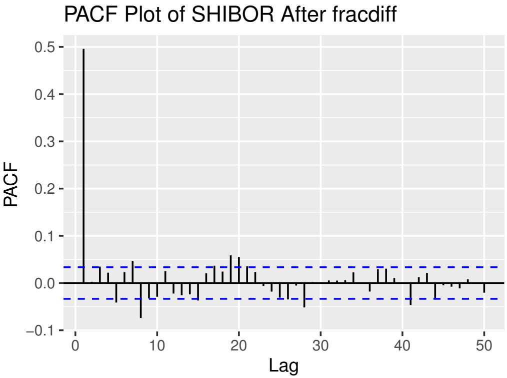
$$\psi(L)=1-\psi_1 L-\psi_2 L^2-\psi_3 L^3-\cdots-\psi_p L^p$$
$$\theta(L)=1-\theta_1 L-\theta_2 L^2-\theta_3 L^3-\cdots-\theta_q L^q$$
$$(1-L)^d=\sum_{k=0}^{\infty}\frac{\Gamma(k-d)}{\Gamma(-d)\Gamma(k+1)}L^k$$

SHIBOR after `fracdiff` from 2006 to 2020



ACF & PACF Plot of SHIBOR after `fracdiff` from 2006 to 2020

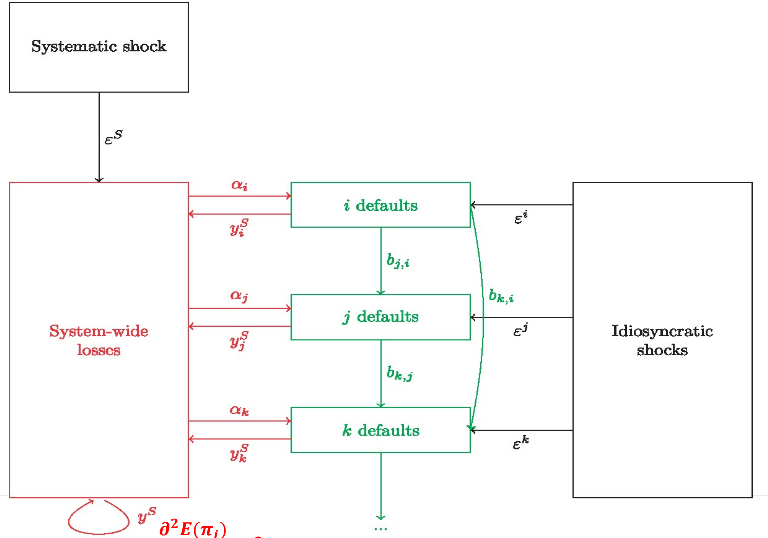




Research Proposal

Identify and Prevent Systemic Risk Based on Financial Network

The framework of systemic risk (Benoit et al., 2016)



Amplification $\dfrac{\partial^2 E(\pi_i)}{\partial \varepsilon^S \partial y^S} > 0$ Contagion $Cov(\pi_i, \pi_j \mid \varepsilon^S = 0) > 0$

Preliminary notations

- Consider N financial institutions indexed by i, each with a risk exposure x_i.
- A proportion α_i of the exposure concerns a systematic risk factor, while $1 - \alpha_i$ concerns a risk factor idiosyncratic to i.
- Denote $y_i^S = \alpha_i x_i$ the systematic exposure and $y_i^I = (1 - \alpha_i)\, x_i$ the idiosyncratic exposure of institution i.
- Denote $y^S = \sum_{i=1}^N y_i^S$ the cumulative exposure to systematic risk for all institutions.
- Direct "links" among financial institutions, given by the $N \times N$ matrix B, whose elements $b_{i,j}$ denote how much i is exposed to j.

Preliminary notations

- The returns on the systematic and i's idiosyncratic factors are $\rho^S + \varepsilon^S$ and $\rho^i + \varepsilon^i$, respectively, where ρ^S and ρ^i are constants, while ε^S and all the ε^i are independently distributed random variables with zero mean.

- We define the benchmark payoff $\hat{\pi}_i$ as what i would receive if there were no other financial institutions in the system and write it in general as $\hat{\pi}_i\left(y_i^S, y_i^I, \varepsilon^S, \varepsilon^i\right)$.

$$\hat{\pi}_i = \left(\rho^S + \varepsilon^S\right) \times y_i^S + \left(\rho^i + \varepsilon^i\right) \times y_i^I. \tag{8}$$

Systemic and Systematic Risk

- Since all institutions are exposed to the systematic factor, they can all suffer losses simultaneously simply because a large negative shock ε^S occurs. We call this form of risk *systematic risk*.

- However, there is more to systemic risk than just systematic risk. As i belongs to a system of financial institutions, its actual payoff differs from $\hat{\pi}_i$ and depends on the exposures of other institutions, the idiosyncratic shocks they face, and on the links of i with other institutions, or even among these other institutions.

- Denoting π_i the actual payoff of i, $\mathcal{E}^I$, Y^S, and Y^I, the $N \times 1$ vectors of idiosyncratic shocks, systematic exposures, and idiosyncratic exposures, respectively, π_i writes as $\pi_i\left(Y^S, Y^I, B, \varepsilon^S, \mathcal{E}^I\right)$. A defining characteristic of systemic risk is that

$$\pi_i\left(Y^S, Y^I, B, \varepsilon^S, \mathcal{E}^I\right) \neq \hat{\pi}_i\left(y_i^S, y_i^I, \varepsilon^S, \varepsilon^i\right).$$

Sources of systemic risk

- *Systemic risk-taking mechanisms*: financial institutions take too much systemic risk if they endogenously choose an exposure x_i and its systematic component $\alpha_i x_i$ that are higher than the welfare-maximizing values of these variables.

- *Contagion mechanisms*: the payoffs of two institutions are positively correlated, even when there is no systematic shock:

$$\mathrm{Cov}\left(\pi_i, \pi_j \mid \varepsilon^S = 0\right) > 0 \tag{9}$$

- *Amplification mechanisms*: the effect of a systematic shock ε^S is greater when the cumulative exposure to this shock y^S is larger:

$$\frac{\partial^2 \mathbb{E}\left(\pi_i\right)}{\partial \varepsilon^S \partial y^S} > 0 \tag{10}$$

My proposed research area—Theoretical Part

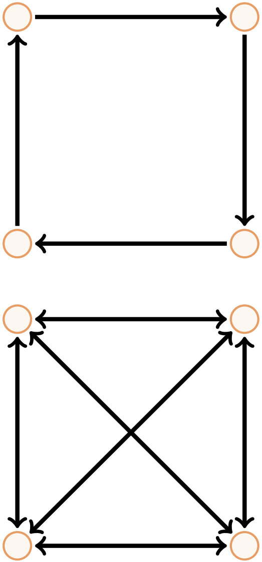
- My theoretical interest focuses on the consequences of different topologies of the exposure network for the impact of a particular institution's failure, building on Jackson and Zenou (2015).
- This interest stems from the increasingly important role played by the precise topology of exposure linkages, the particular way the banking system is wired at a particular moment in time, which means that it is not sufficient to study institutions in isolation.

Relevant literature in this field of study

- Allen and Gale (2000) studies an example in which banks in four different regions face negatively correlated liquidity shocks.

- Contagion can spread more easily if the network topology is an incomplete network meaning that the exposure network has the form of a circular exposure of one region against its neighboring region.

- If the regions are fully connected (a complete network), the network is more resilient in absorbing losses.



Future Development

- Incorporate into the model the differences between deposit-taking institutions, investment banks, and other specialized financial institutions such as hedge funds.

- Consider the endogenous formation of financial networks and their efficiency and policy implications: Banks may endogenously form linkages with one another in order to insure against the risk of contagion.
  - Banks can succeed in forming networks that are highly resilient to the propagation of shocks. (Babus, 2016).

My proposed research area — Empirical Part

- Discover the structural features of the interbank exposure network.
- Identify the form of systemic failure facing these networks.
- e.g. the interbank exposure networks which have a core-periphery structure with heavy-tailed degree and exposure-size distributions will be quite resilient to random disruptions but highly vulnerable to disruptions in hubs (Boss et al., 2004).

Relevant study in this field of study

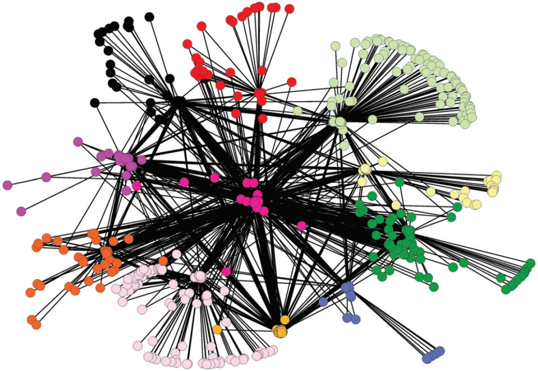
- Boss et al. (2004) studies the network topology of Austrian interbank exposure network.

- The exposure network maps interbank debts between 900 Austrian banks, the OeNB, and an aggregate node representing all exposures outside Austria.

- The Austrian banking system has a two-tiered structure with core or head institutions of various banking groups, placed mainly in the capital Vienna, and a periphery of local banks belonging to these groups, placed mainly in the countryside and the Austrian federal states.

Austrian network of 2002

- There are only a few institutions with many exposures and many institutions with only a few.
  - in- and out-degree distributions are skewed to the left and heavy tailed.
- There is only a small degree of clustering in the interbank network.
  - The probability that two banks that have a link to any given bank are also themselves connected is small.



Similar network structures in different countries

- for Brazil, Cont et al. (2010),
- for Germany, Craig and Von Peter (2014),
- for the United Kingdom, Langfield et al. (2014),
- in an international context, Von Peter (2007).

Difficulty in the empirical analysis

- Lack of observations
  - Due to various forms of rescue operations of the authorities in the severe banking crisis
- Solution:
  - SIMULATION STUDIES.

Simulation Studies — Existing literature

- A pioneering paper by Furfine (2003) fixates on the counterparty default and contagion in *payment systems*,

- Papers regarding *banking systems* using many datasets around the world (Upper and Worms, 2004, Wells, 2004, Elsinger et al., 2006a,b).

- These simulation studies have two main findings:
  1. Contagion of insolvency due to interbank exposures is rare,
     - ✓ studies working with both idiosyncratic bank failures and exogenous recovery rates (Amundsen and Arnt, 2005, Furfine, 2003, Lublóy, 2005, Upper and Worms, 2004, Wells, 2004),
     - ✓ studies working with correlated exposures and shocks to the asset values (Elsinger et al., 2006a,b, Cont and Wagalath, 2013, Alessandri et al., 2018).
  2. The probability of contagion happening in the worst cases is relatively high.
     - ✓ there is little contagion for low bankruptcy costs, but as total assets are destroyed up to an amount of 30% and more, the number of contagious defaults increases sharply. Elsinger et al. (2006a)

THANK YOU VERY MUCH !!!

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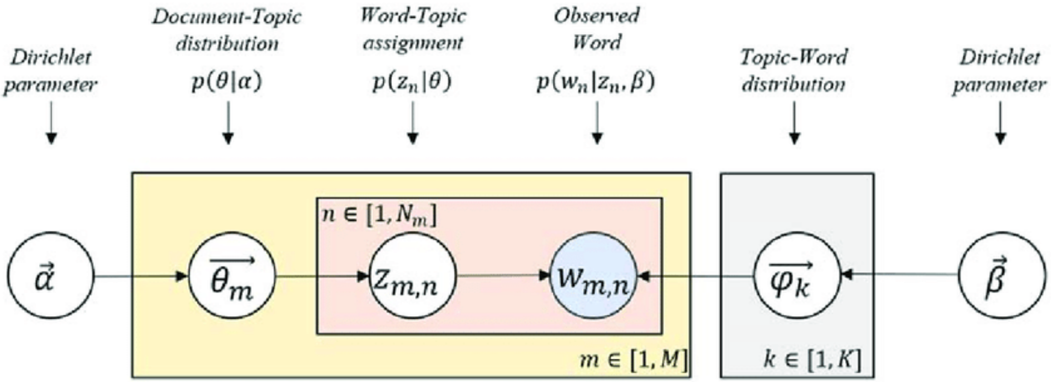
Appendix

Topic Modelling using Latent Dirichlet Allocation

Latent Dirichlet Allocation

- Two jars of dice, one containing the `doc-topic` dice and the other `topic-word` dice.
- The God randomly chooses K dice from the second jar and indexes them form 1 to K.
- The way of creating a new document— repeat the following process:
  (i) The God randomly chooses a `doc-topic` dice first.
  (ii) He then throws the `doc-topic` dice and gets a topic z
  (iii) He finally chooses the z dice from K `topic-word` dice, throwing it and getting a word.

Vector space of LDA



Topic modelling using Louvain community detection algorithm

Origin and Rationale of Louvain Algorithm

- stems from Blondel et al. (2008),
- aims to find high modularity partitions of large networks in a short time and that unfolds a complete hierarchical community structure for the network.

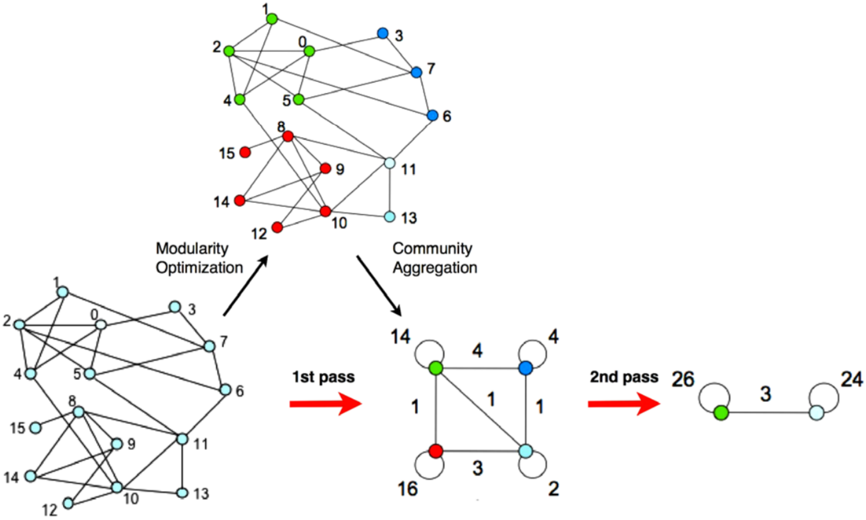
Two phases

- 1st
  - N nodes.
  - Assign a different community to each node of the network.
  - For each node i, we consider the neighbour j of i and evaluate the gain
    (a) by removing i from its community
    (b) by placing it in the community of j

$$\Delta Q = \left[\frac{\sum_{\text{in}} + 2k_{i,\text{ in}}}{2m} - \left(\frac{\sum_{\text{tot}} + k_i}{2m}\right)^2\right] - \left[\frac{\sum_{\text{in}}}{2m} - \left(\frac{\sum_{\text{tot}}}{2m}\right)^2 - \left(\frac{k_i}{2m}\right)^2\right]$$

- 2nd
  - Nodes are now communities found during the first phase.
  - Weights of the links between the new nodes are given by the sum of the links between nodes in the corresponding two communities.
  - Links between nodes of the same community lead to self-loops for this community in the new network.

Two phases


Modularity
Optimization
Community
Aggregation
1st pass
2nd pass
14
4
4
1
1
1
3
16
2
26
3
24

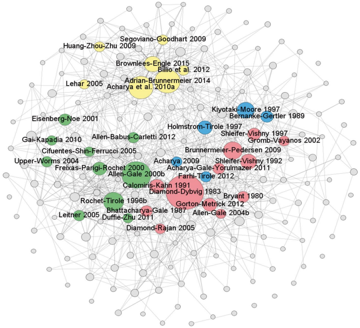
Topic modelling using Louvain algorithm

- Aims: Take words as nodes and the final clusters as topics.
- Procedure:
  - Construct the matrix, the element (i, j) of which is the number of word j in the document i.
  - Calculate the cosine similarity between two words and take it as the weight between two words.
$$\frac{D_j' D_i}{\|D_i\| \, \|D_j\|}$$
  - using the Louvain algorithm to get clusters (aka topics).

Identify systematically important literature

Systematically important literature

- The size of each circle is proportional to the number of times each article is cited by other articles in the survey.
- The edges represent citations.
- The position of nodes is based on the Fruchterman–Reingold algorithm.
- The strand of the literature they belong to:
  - risk-taking (blue/right),
  - amplification mechanisms (red/bottom),
  - contagion (green/left),
  - systemic risk measures (yellow/top).

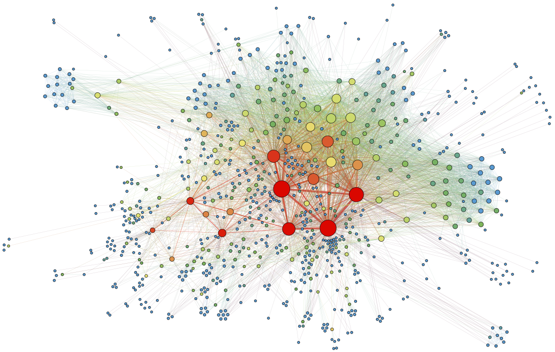


Force-directed layout algorithm

- The sum of the force vectors determines which direction a node should move. The step width, which is a constant, determines how far a node moves in a single step.

- When the energy of the system is minimized, the nodes stop moving and the system reaches it's equilibrium state.

- But there is no guarantee that the system will reach equilibrium at all.



Fruchterman-Reingold Algorithm

- Fruchterman and Reingold (1991) introduced a “global temperature” that controls the step width of node movements and the algorithm’s termination.

- The step width is proportional to the temperature, so if the temperature is hot, the nodes move faster (i.e, a larger distance in each single step).

- This temperature is the same for all nodes, and cools down at each iteration. Once the nodes stop moving, the system terminates.