Personal Profile

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Lingnan College, Sun Yat-sen University

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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 present,

- Exchange in **Warwick Business School, University of Warwick** from Sep 2019 to Dec 2019.

Research Interests

Research Fields of interest in Finance

1. **Financial Economics**
   - **Zeng, Yan, Xuefeng Wu, Junqing Kang, and Zhuoran Chen, 2023. Optimal Coupon Cooperation Policy of E-commerce Platforms and E-tailers and Its Benefit. Systems Engineering – Theory & Practice, 43(1): 110-134**,
   - Does the rapid urban technological progress aggravate the demand for rural products in China?— Based on the price effect and the common prosperity effect.

2. **Financial Econometrics**
   - Zhou, Xianbo and Zhuoran Chen, 2023. The Impact of Uncertainty Shocks to Consumption under Different Confidence Regimes Based on a Stochastic Uncertainty-in-Mean TVAR Model. Sustainability, 15(4): 3032.

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

Research Papers

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

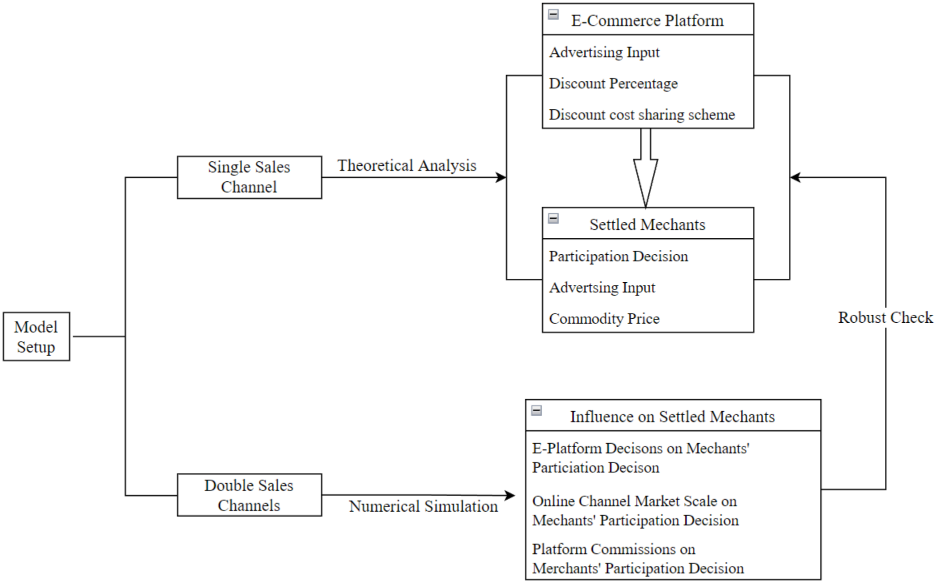
- Issuing consumption coupons cooperatively by e-commerce platforms and their merchants is recently an innovative and promising trend in platform economy.

- 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)?

Framework

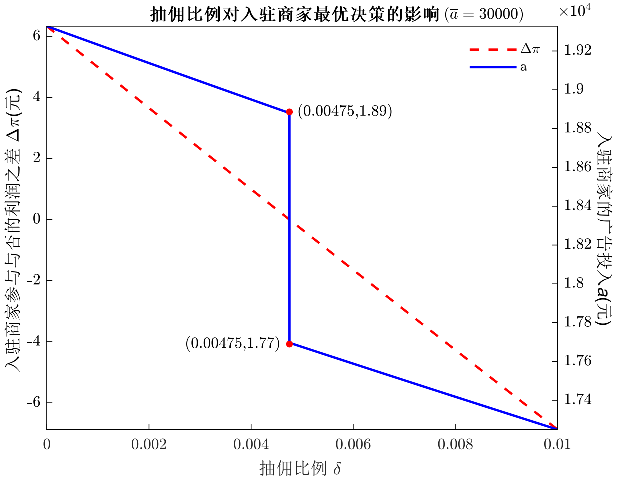

E-Commerce Platform
Advertising Input
Discount Percentage
Discount cost sharing scheme
Single Sales Channel
Theoretical Analysis
Settled Mechants
Participation Decision
Advertsing Input
Commodity Price
Model Setup
Robust Check
Influence on Settled Mechants
E-Platform Decisons on Mechants' Particiation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

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,

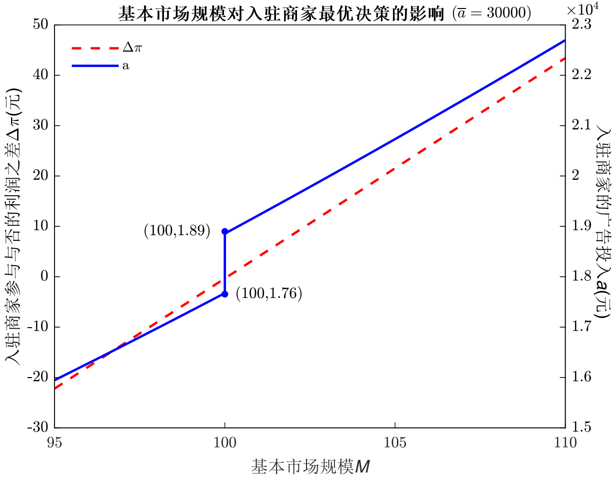


Results I

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,

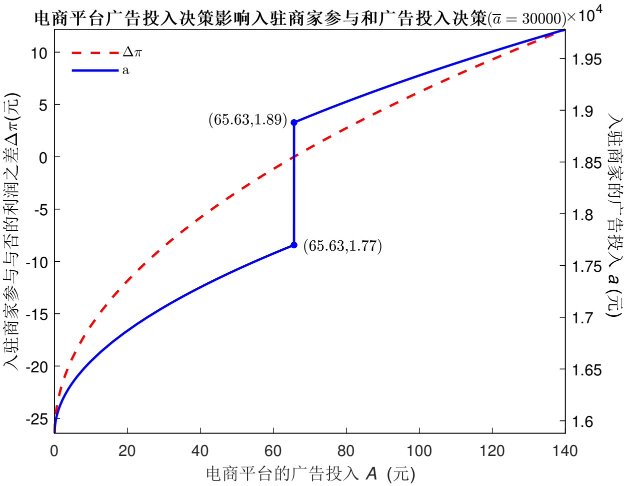


Results I

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

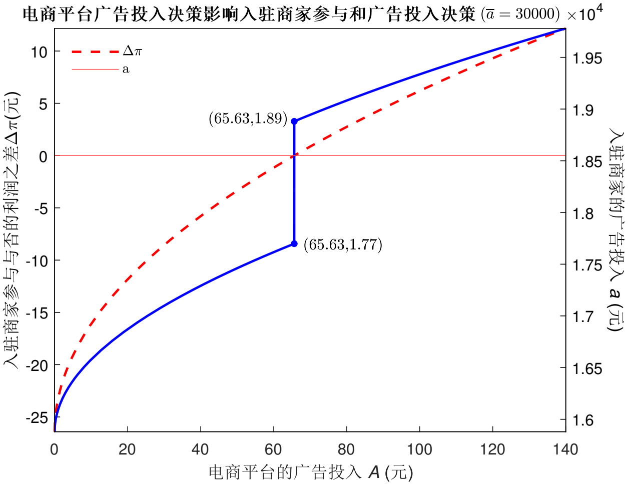
- the platform commissions decrease,
- the market scale of merchants' platform sales channel increases,
- the advertisements input of e-commerce platform increases.



Results II

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

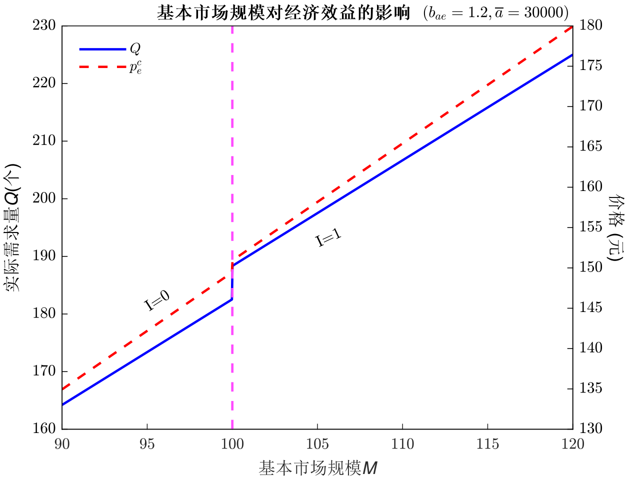
A1 There is a positive correlation between participation decision and advertisements input.



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.



Published

The Impact of Uncertainty Shocks to Consumption under Different Confidence Regimes

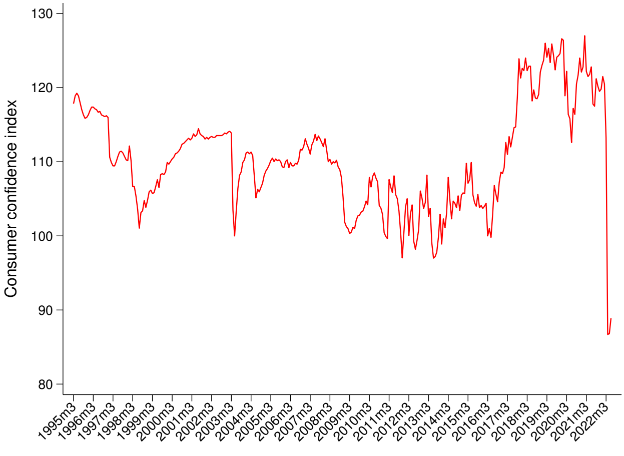
—Based on a Stochastic Uncertainty-in-Mean TVAR Model.

Xianbo ZHOU, **Zhuoran CHEN**

(Lingnan College, Sun Yat-sen University)

Motivation

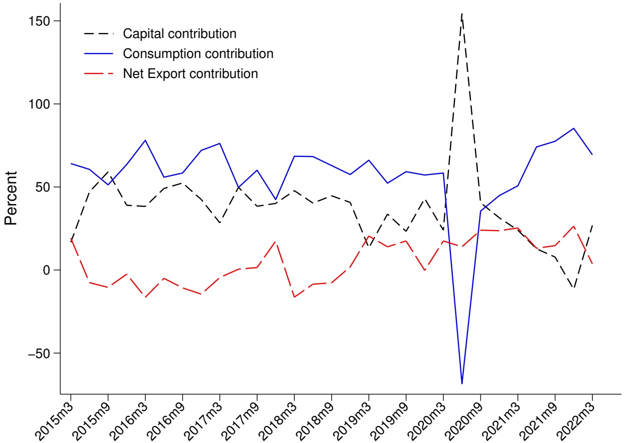
- Volatile Chinese consumer confidence (CCI), $\Rightarrow$



Motivation

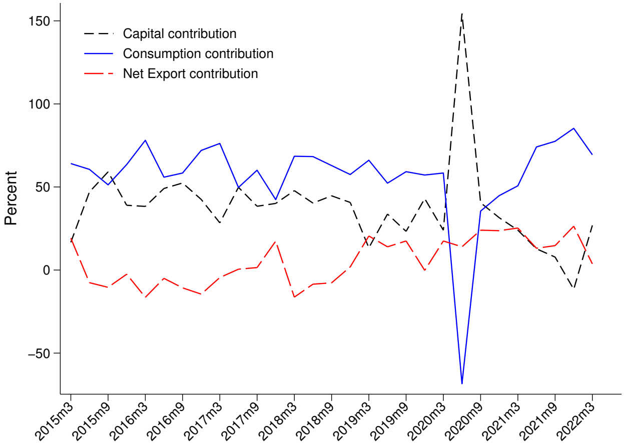
- Volatile Chinese consumer confidence (CCI), $\Rightarrow$

- 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

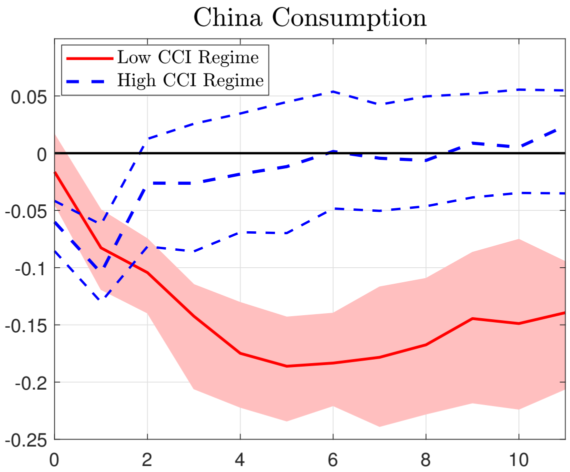
$$
\tilde{S}_t = 1 \left\{ CCI_{t-d} \leq Z^* \right\}
$$

Results I

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

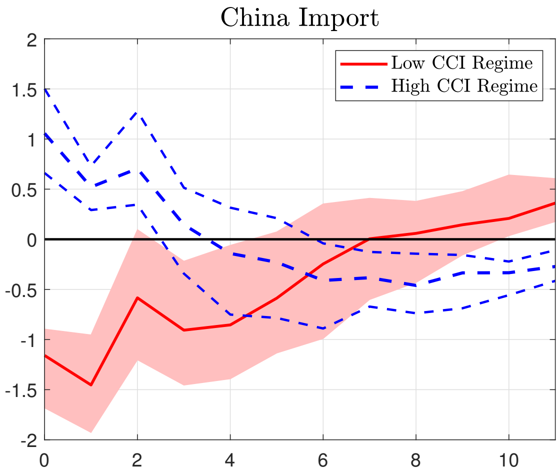
Results I

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



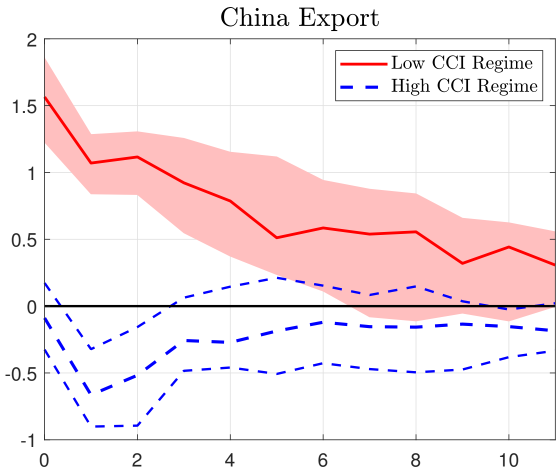
Results I

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



Results I

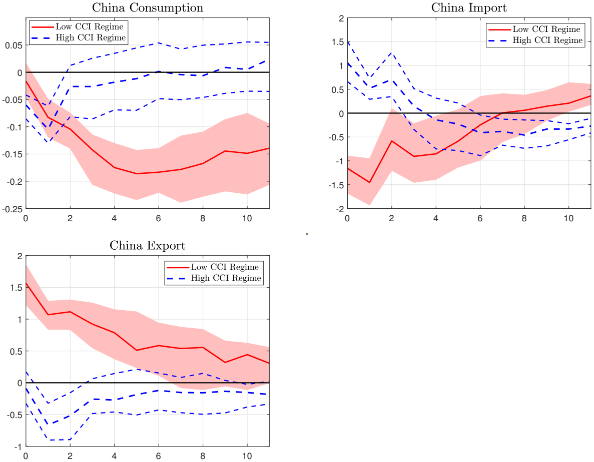
- In China, compared to high CCI, low CCI will
  - exacerbate domestic consumption,
  - deteriorate import,
  - benefit export.



Results I

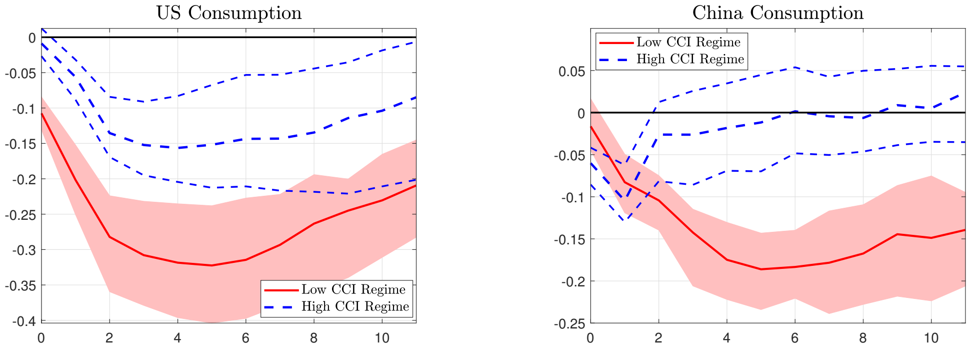
- In China, compared to high CCI, low CCI will
  - exacerbate domestic consumption,
  - deteriorate import,
  - benefit export.

- 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

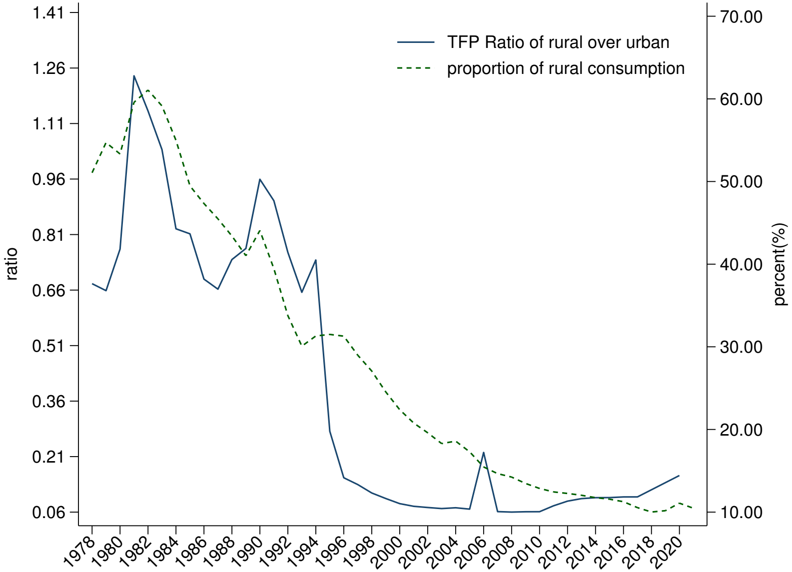
- Consumer confidence is much more influential in US than China.



Does the rapid urban technological progress aggravate the demand for rural products in China?

— 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
1978
1980
1982
1984
1986
1988
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2012
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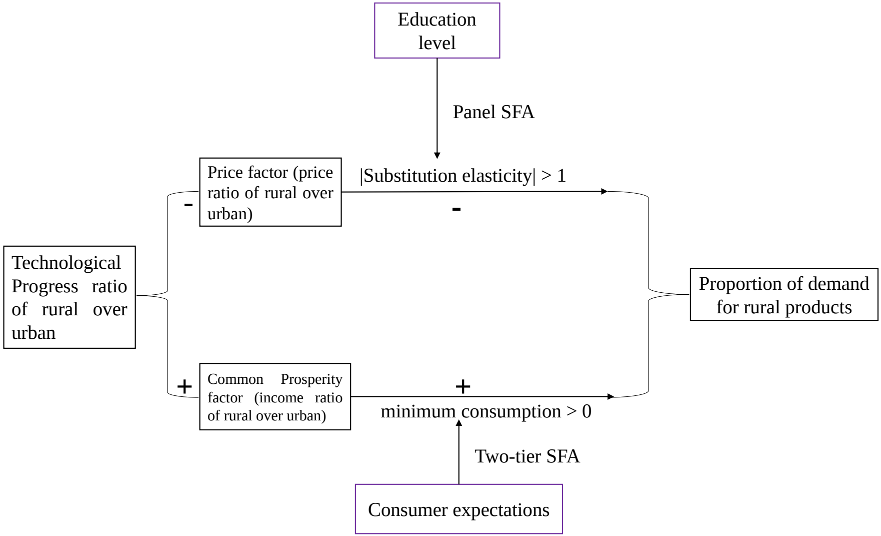
2016
2018
2020

Framework


Education level
Panel SFA
Price factor (price ratio of rural over urban)
|Substitution elasticity| > 1
-
-
Technological Progress ratio of rural over urban
Proportion of demand for rural products
+
Common Prosperity factor (income ratio of rural over urban)
+
minimum consumption > 0
Two-tier SFA
Consumer expectations

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

- Since

$$\frac{P_1\left(c_1+\overline{c_1}\right)}{P_2\left(c_2\right)}=\frac{\omega_1}{\omega_2}\left(\frac{P_1}{P_2}\right)^{1-\epsilon}\Rightarrow\frac{A_1L_1+\overline{c_1}}{A_2L_2}=\frac{\omega_1}{\omega_2}\left(\frac{w_2A_1}{w_1A_2}\right)^{\epsilon}$$

- Proportion of rural consumption x_1^c

$$x_1^c=\frac{\frac{\omega_1\delta^{1-\epsilon}}{\omega_2}LA_1-\overline{c_1}\xi}{(1-\xi)\overline{c_1}+\left(1+\frac{\omega_1\delta^{1-\epsilon}}{\omega_2}\right)LA_1} \tag{6}$$

- Since we normalize $A_1=1$ in order to find out the impact of relative urban tech progress A_2/A_1, equation 6 turns out to be

$$x_1^c=\frac{\frac{\omega_1\delta^{1-\epsilon}}{\omega_2}L-\overline{c_1}\xi}{(1-\xi)\overline{c_1}+\left(1+\frac{\omega_1\delta^{1-\epsilon}}{\omega_2}\right)L}\Rightarrow\frac{\partial x_1^c}{\partial\xi}=\frac{-\overline{c_1}\left(L+\overline{c_1}\right)}{\left((1-\xi)\overline{c_1}+\left(1+\frac{\omega_1\delta^{1-\epsilon}}{\omega_2}\right)L\right)^2}$$

- Enlarging of income gap between urban and rural sectors may shrink the proportion of demand for rural products.

Financial Crisis and Financial Network Stability[1]

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

[1] Acemoglu, Daron, Asuman Ozdaglar, and Alireza Tahbaz-Salehi. 2015. "Systemic Risk and Stability in Financial Networks." *American Economic Review*, 105 (2): 564-608.

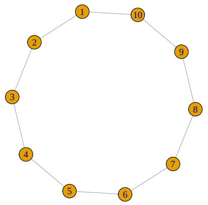
Motivation

- Increasingly intricate interdependencies among financial institutions in different countries may increase the possibilities of financial tsunamis,

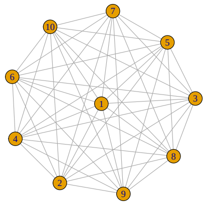
- Different structures of a financial network may affect the contagion of risks among its nodes (i.e. different financial institutes).

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).



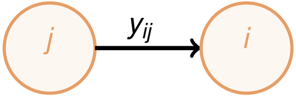
- In the context of input-output economies with linear interactions, sparsity is *not relevant*. Rather it is the symmetry that matters.
    - Acemoglu et al. (2012).

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.

Small Shock Regime

Proposition

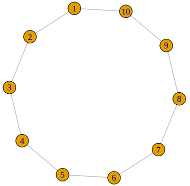
There exist ϵ^* and y^* such that for all $\epsilon < \epsilon^*$ and $y > y^*$,

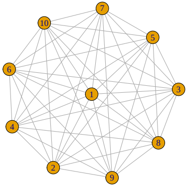
(a) *the complete financial network is the most stable and most resilient,*

(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

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.

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.

How does WHO warn the world?[2]

—Based on two-stage dynamic Bayesian persuasion game

[2] Alizamir, Saed, Francis de Véricourt, and Shouqiang Wang. 2022. "Warning against recurring risks: An information design approach." Management Science 66 (10): 4612-4629.

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.

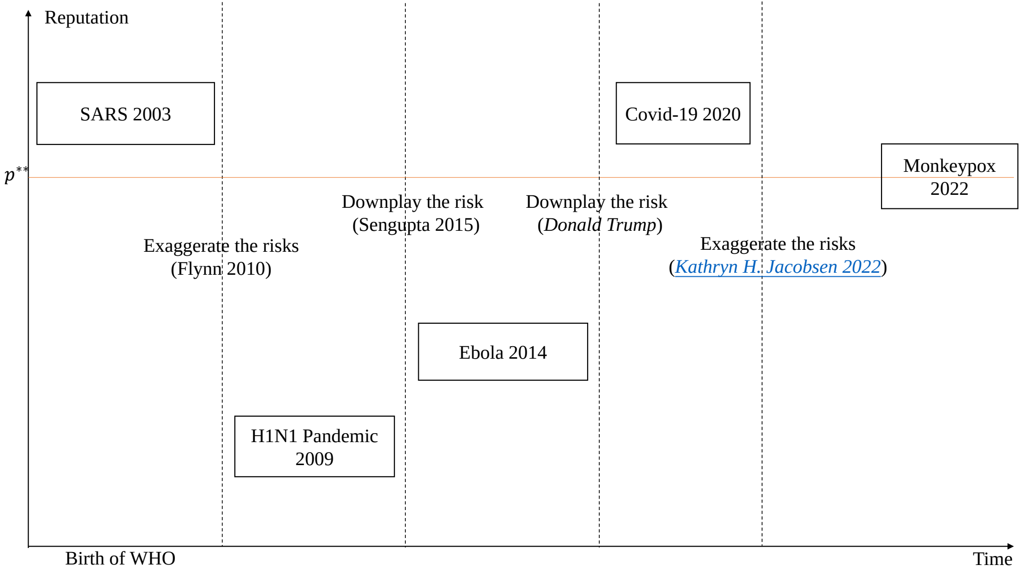
The game

- 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
p^{**}
SARS 2003
Covid-19 2020
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

Insights

- WHO's success in tackling the 2003 SARS outbreak led to the revision of the International Health Regulations (World Health Organization 2005), which made WHO the key coordination agency to collect information about and prevent public health risks. Given this high level of credibility, my model predicts that the agency should exaggerate the signal it receives. This is exactly what WHO was accused of doing after it declared its first PHEIC for the 2009 flu pandemic.This, in turn, seemed to have damaged WHO's credibility. My model predicts that the agency should then downplay the risk, which is, again, what the agency was accused of doing when it refrained from declaring a PHEIC for the 2014 Ebola outbreak. Nonetheless its credibility didn't go high enough (above p^{**} in the model) so it had to consider its future credibility which is why it downplayed this Covid-19 pandemic.

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.

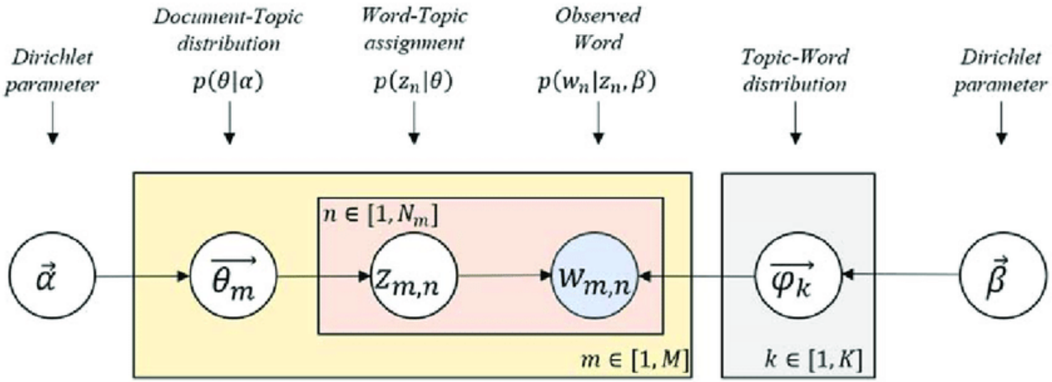
- The way of creating a new document— repeat the following process:
  (i) The God randomly chooses a `doc-topic` dice first.
  (ii) He then throws the `doc-topic` dice and gets a topic z
  (iii) He finally chooses the z dice from K `topic-word` dice, throwing it and getting a word.

$$p(\vec{w}, \vec{z} \mid \vec{\alpha}, \vec{\beta}) = p(\vec{w} \mid \vec{z}, \vec{\beta}) p(\vec{z} \mid \vec{\alpha})$$

$$= \prod_{k=1}^{K} \frac{\Delta\left(\vec{\phi}_K + \vec{\beta}\right)}{\Delta(\vec{\beta})} \prod_{m=1}^{M} \frac{\Delta\left(\vec{\theta}_m + \vec{\alpha}\right)}{\vec{\alpha}}$$

$$P(\boldsymbol{W}, \boldsymbol{Z}, \boldsymbol{\theta}, \boldsymbol{\phi}; \alpha, \beta) = \prod_{i=1}^{M} P\left(\theta_j; \alpha\right) \prod_{i=1}^{K} P(\phi; \beta) \prod_{t=1}^{N} P\left(Z_{j,t} \mid \theta_j\right) P\left(W_{j,t} \mid \phi z_{j,t}\right)$$

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 of Louvain Algorithm I

- Assume that we start with a weighted network of N nodes.

- First, we assign a different community to each node of the network. So, in this initial partition there are as many communities as there are nodes.

- Then, for each node i we consider the neighbours j of i and we evaluate the gain of modularity that would take place by removing i from its community and by placing it in the community of j.

- The node i is then placed in the community for which this gain is maximum (in the case of a tie we use a breaking rule), but only if this gain is positive. If no positive gain is possible, i stays in its original community. This process is applied repeatedly and sequentially for all nodes until no further improvement can be achieved and the first phase is then complete.

Two phases of Louvain Algorithm II

- The second phase of the algorithm consists in building a new network whose nodes are now the communities found during the first phase. To do so, the weights of the links between the new nodes are given by the sum of the weight of the links between nodes in the corresponding two communities.

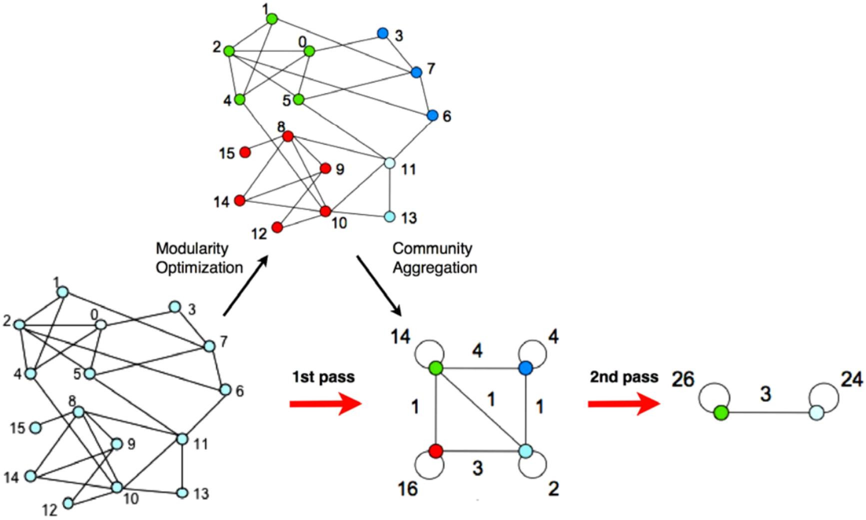
Two phases

- 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
1
2
0
3
7
4
5
6
8
15
9
11
14
10
13
12
14
4
4
1
1
1
16
3
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.

$$\frac{D_j' D_i}{\|D_i\| \, \|D_j\|}$$

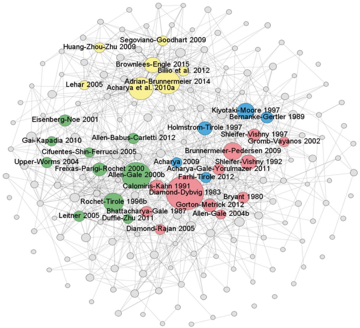
  - using the Louvain algorithm to get clusters (aka topics).

Fruchterman-Reingold Algorithm

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).

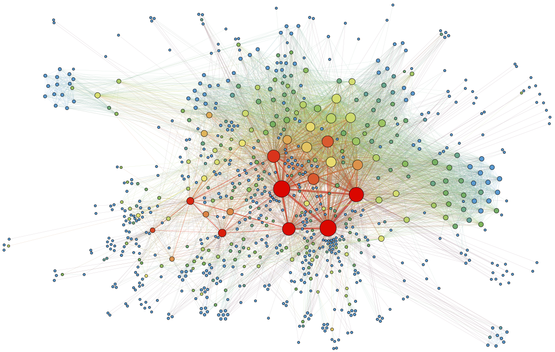


Force-directed layout algorithm

- 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.

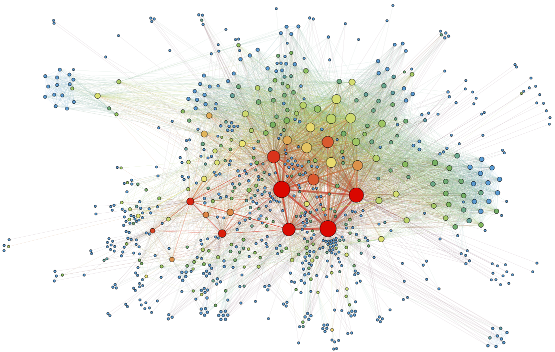


Fruchterman-Reingold Algorithm

- 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.



Force-directed layout algorithm

- stems from the pioneer work Fruchterman and Reingold (1991).
- The Fruchterman-Reingold Algorithm is a force-directed layout algorithm. The idea of a force directed layout algorithm is to consider a force between any two nodes. In this algorithm, the nodes are represented by steel rings and the edges are springs between them. The attractive force is analogous to the spring force and the repulsive force is analogous to the electrical force. The basic idea is to minimize the energy of the system by moving the nodes and changing the forces between them.

Force-directed layout algorithm

- In this 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. The drawback of this is that if we define a constant step width, there is no guarantee that the system will reach equilibrium at all. T.M.J. Fruchterman and E.M. Reingold 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.