Reducing Systemic Risk in Financial Networks through Donations

Extended Abstract

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ABSTRACT

We examine the extent to which rescue strategies within a banking system can reduce systemic risk. We focus on donations from solvent banks to banks in distress, which can in principle reduce losses and prevent default cascades. We build an agent-based model to simulate the ensuing strategic game on a randomly generated financial network, where nodes represent banks and edges represent interbank liabilities. Each bank independently decides whether to rescue (and whom) to maximise their payoffs. We analyse the rescue strategies adopted by the banks at equilibrium, using empirical game-theoretic analysis. Our results show that donations can indeed reduce systemic risk when the equilibrium strategy profile is adopted. Individual donations can benefit multiple banks in the network. Our results also indicate that lower default costs and small-variance liabilities tend to decrease the incentives to donate. We furthermore examine the impact of the banks' rationality on the effects of rescue, finding that banks behaving rationally use their funds for rescues more efficiently than banks that behave irrationally.

KEYWORDS

Financial Networks; Systemic Risk; Agent-Based Modelling; Empirical Game-Theoretic Analysis

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1 INTRODUCTION

Reducing systemic risk often requires saving a number of banks in the banking network. As we witnessed throughout history, this comes at huge expenses to the taxpayer or investors, with large bailouts or shady acquisitions of the bank in distress. We wonder whether the network can "self-heal" in an incentive-compatible way. The idea we consider is the donation of funds from certain banks to banks in distress to rescue them, reducing the losses of their creditor banks. In a complex banking system, a creditor bank with limited funds may have several insolvent debtors, and on the other hand, an insolvent bank may have several potential rescuers, so the rescue strategy of a bank depends not only on its local information but also on other banks' strategies, thus defining a strategic game.

Our main contributions can be summarised as follows:

(1) an agent-based simulation framework supporting strategic analysis of individual rescues in the banking system;
(2) empirical validation of the existence of equilibrium in the donation game, and a series of sensitivity analyses based on empirical parameters; and
(3) analysis of incentives and the impact of banks' rationality on their behaviour in the donation game.

Related Work. Eisenberg and Noe were the first to model banks with balance sheets and define them on a network [2]. Rogers and Veraart extended this model by adding default costs to the banking network, in which insolvent banks can only recover a fraction (rather than all) of their assets to transfer to their creditors [9]. Based on the Eisenberg-Noe model and its extensions, a series of works on stress test methods has been conducted [1, 3]. However, Upper claimed that traditional stress test methods only analyse static balance sheets, leading to limited conclusions without agents' strategic interactions [10]. Some recent studies have considered the application of game-theoretic analysis to agents' interactions in the systemic risk scenario [4, 5, 7], but individual donations, which is the focus of the present paper, has not been widely studied.

2 DONATION GAME

We work with a randomly generated banking network and choices of external asset parameters $e \in \{0.0, 0.2, \cdots, 7.8, 8.0\}$. The donation game starts with a set of banks $N = \{1, \cdots, 10\}$ and each bank is given an external asset $e_i = e$, defining the *external asset vector* $\boldsymbol{e}$. The notional of an interbank liability of bank i to bank j is the absolute value of a random number following the standard normal distribution, i.e., $l_{ij} = |z|, z \sim N(0,1), \forall i, j \in N, i \neq j$, and we assume $l_{ii} = 0, \forall i \in N$. As a result, we obtain the *liabilities matrix* $\boldsymbol{L}$ comprising all the liability data in the generated banking network. The *relative liabilities matrix* $\boldsymbol{\Pi}$ is defined by

$$\pi_{ij} = \begin{cases} \frac{l_{ij}}{L_i} & \text{if } L_i > 0, \\ 0 & \text{otherwise.} \end{cases}$$

A *clearing vector* $\boldsymbol{\Lambda}$ representing actual payments of banks is a vector such that $\boldsymbol{\Lambda} = \Phi(\boldsymbol{\Lambda})$ where function Φ is given by

$$\Phi(\boldsymbol{\Lambda})_i = \begin{cases} L_i & \text{if } e_i + \sum_{j \in N} \pi_{ji} \Lambda_j \geq L_i, \\ a e_i + b \sum_{j \in N} \pi_{ji} \Lambda_j & \text{otherwise.} \end{cases}$$

where $a, b \in \{0.1, 0.3, 0.5, 0.7, 0.9\}$ are two constants called *recovery parameters*, controlling the fraction of the nominal value of assets for liquidation. We use the Greatest Clearing Vector Algorithm (GA) [9] to calculate the greatest clearing vector for a banking network.

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The *value* of a bank is defined as the difference between its actual total assets and its total liabilities, that is $v_i = e_i + \sum_{j\in N} \pi_{ji}\Lambda_j - L_i$. A bank is considered *insolvent* if its value is negative, that is $v_i < 0$.

2.1 Donations

A *donation* is viewed as an asset transfer from one bank to another. We make several assumptions to simplify the model. Firstly, only solvent banks can donate to insolvent banks. Secondly, the donation amount is always set to the opposite number of the insolvent bank's value, that is $d_{ij} = -v_j, v_j < 0$. Thirdly, a donation is valid only if the donor's external asset can cover the donation amount. Finally, we assume that each donor can select at most one recipient. These assumptions keep our experiments computationally feasible.

The choice of insolvent bank is referred to as the *strategy* of the donor. For example, strategy $s_i = j$ implies the donation $d_{ij} = -v_j$. Note that a solvent bank can also choose not to donate, which we write as $s_i = \emptyset$. A *strategy profile* $\boldsymbol{s} = (s_1, \cdots, s_{10})$ is a specification of a strategy for each of the banks. Each strategy profile corresponds to a unique *donation matrix* $\boldsymbol{D}(\boldsymbol{s})$, where the entry d_{ij} is given by

$$d_{ij} = \begin{cases} -v_j & \text{if } s_i = j, \\ 0 & \text{otherwise.} \end{cases}$$

With the donation matrix, the external asset vector is updated by

$$e(\boldsymbol{s})'_i = \begin{cases} e_i - d_{ij} & \text{if } s_i = j \text{ and } e_i \geq d_{ij}, \\ e_i + d_{ji} & \text{if } s_j = i \text{ and } e_j \geq d_{ji}, \\ e_i & \text{otherwise.} \end{cases}$$

Again we use the GA algorithm to calculate the bank values after donations, denoted by $v(\boldsymbol{s})'_i$. Then, the *payoff* of a bank is given by

$$p(\boldsymbol{s})_i = \begin{cases} v(\boldsymbol{s})'_i - v_i & \text{if } s_i = j \text{ and } e_i \geq d_{ij} \text{ or } s_i = \emptyset, \\ -\infty & \text{if } s_i = j \text{ and } e_i < d_{ij}. \end{cases}$$

Once we obtain the payoffs of all banks in all strategy profiles, we compute the equilibrium of the induced empirical game by the α-Rank algorithm [8]. Since the equilibrium is in the form of a probability distribution over strategy profiles, we calculate the weighted average data with it, which indicates the expected banks' behaviour. The experiments will be repeated 100 times to eliminate the impact of the randomness of the generated banking networks.

2.2 Rationality

In the α-Rank algorithm, we replace the original definition of the fixation probability of player i from strategy σ to τ (see [8] for more details) with the following definition from OpenSpiel [6]:

$$\rho^i_{\sigma,\tau}(\boldsymbol{s}_{-i}) = \begin{cases} \epsilon & \text{if } f(\tau, \boldsymbol{s}_{-i}) < f(\sigma, \boldsymbol{s}_{-i}) \\ 0.5 & \text{if } f(\tau, \boldsymbol{s}_{-i}) = f(\sigma, \boldsymbol{s}_{-i}) \\ 1-\epsilon & \text{if } f(\tau, \boldsymbol{s}_{-i}) > f(\sigma, \boldsymbol{s}_{-i}) \end{cases}$$

where $\boldsymbol{s}_{-i}$ denotes the strategies of other players, $f(\sigma, \boldsymbol{s}_{-i})$ and $f(\tau, \boldsymbol{s}_{-i})$ capture i's payoffs using strategy σ and τ respectively, and $\epsilon \in (0, 0.5]$ denotes the minimal fixation probability. ϵ can be considered a parameter to measure the agents' rationality. Specifically, when $\epsilon = 0.5$, a strategy switch occurs randomly, and when $\epsilon \to 0$, the agents will be very rational as a tiny difference in payoffs will lead to a strategy switch. Therefore, we can study how the rationality of banks affects their rescue behaviour by using different *rationality parameters* $\epsilon \in \{0.001, 0.01, 0.1, 0.3, 0.5\}$.

3 RESULTS OVERVIEW

Effects of Rescue. Our experimental results prove that donations can indeed reduce systemic risk. we also find that the reduction in defaults can be larger than the number of donations, which indicates that one donation can rescue more than one insolvent bank in some cases. The reason is that the increase in the values of the rescued banks can generate a positive externality, increase the values of other banks, and save more insolvent banks in this way.

Impacts of Model Parameters on Rescue. We studied how the model parameters affect the effectiveness of rescue by experimenting with different external asset parameters and recovery parameters. Our results show that for a pair of fixed recovery parameters, the effects of rescue can reach a peak when the external assets are at a moderate level vis-à-vis the debt notionals. On the other hand, with the increase in recovery parameters, the peak moves towards smaller external assets as the match of assets and debts appears in advance.

Incentives of Rescue. The incentive of a donation can be viewed as the sum of three terms: *cost*, *direct return* from the rescued bank and *indirect return* from the positive externality of other banks. Intuitively, big recovery parameters could increase the incentives of rescue because of the lower cost and the higher indirect return. However, our results reveal a counter-intuitive fact that big recovery parameters may reduce the incentive due to the lower direct return. In addition, we can also observe that the incentive may also diminish with the decrease in relative liabilities, so small-variance liabilities are not conducive to individual rescues, which is the reason why solvent banks may have insufficient motivation to rescue.

Imperfect Rationality. We also studied the impact of rationality on banks' behaviour by adjusting rationality parameters ϵ. Our results show that the amount of donations increases significantly with the increase in ϵ. However, more donations do not necessarily mean higher rescue efficiency. To evaluate the effects of rescue at different rationality levels, we calculate the rescue efficiency by

$$\eta(\boldsymbol{s}) = \frac{n_r(\boldsymbol{s})}{\sum_{i\in N}\sum_{j\in N} d_{ij}}$$

where $n_r(\boldsymbol{s})$ denotes the reduction in defaults due to donations in strategy profile $\boldsymbol{s}$, and d_{ij} refers to the corresponding donation amount. We found that the rescue efficiency when ϵ is large is always higher than that when ϵ is small.

4 CONCLUSION

Our research examined how donation as an individual rescue strategy reduces systemic risk. Our results show that donations can indeed reduce systemic risk when the equilibrium strategy profile is adopted, proving that the banking network can "self-heal" in an incentive-compatible way via donations. We also find that the increase in values and clearing payments of the rescued banks can generate a positive externality, making more than just the rescued banks survive. In addition, more assets available upon default and small-variance liabilities may lower the incentives of rescue, which is the reason that solvent banks may have insufficient motivation to rescue even though they have sufficient funds. Moreover, the more irrational the banks are, the higher the volume of donations, but the lower the rescue efficiency per dollar.

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