



Systemic risk and the financial network system: an experimental investigation

Yudistira Permana¹ · Saiqa Akbar¹ · Anisa Nurpita¹

Received: 7 August 2021 / Revised: 16 December 2021 / Accepted: 22 January 2022 /
Published online: 31 March 2022

© The Author(s) under exclusive licence to Eurasia Business and Economics Society 2022

Abstract

This paper investigates the economic agent behavior when managing a bank in order to avoid a failure when exposed with the financial systemic risk using a lab experiment. We use Chen et al.'s (Oper Res 64:1089–1108, 2016) model to construct the decision problem in the experiment. The model assumes that the systemic risk occurs through two channels: the liquidity channel and the network channel. The former occurs from the external investment shock which is endogenous in the balance sheet. The latter is a function of other banks' clearing repayment; which is also caused by the external investment shock. Given these, there are two intuitive optimal strategies in order to avoid a failure: *imposing a higher external investment interest than that of its risk* and *avoiding the financial interactions with the high-risky banks*. We use students and bankers as our subjects to check the validity of Chen et al.'s optimal strategy given their respective background. Our results show that both students and bankers partially follow Chen et al.'s intuitive optimal strategy: the first strategy. Only the student group is found to follow the second optimal intuitive strategy of Chen et al. In addition, both subject groups have a different behavior in order to avoid the failure.

Keywords Systemic risk · Bank interconnectedness · Behavioral finance · Laboratory experiment

JEL classification C92 · G40 · G11

✉ Saiqa Akbar
saiqailham88@ugm.ac.id

¹ Department of Economics and Business, Vocational College, Universitas Gadjah Mada, Yogyakarta 55281, Indonesia

1 Introduction

The financial systemic risk becomes one main concern in the modern financial system in which it leads to a bankruptcy—of the financial institutions—and economic crisis (Acharya et al., 2017; Hellwig, 2009). We try to put into a context of financial systemic risk where the initial shock of a bank impacts other banks within the same financial network which includes simultaneous financial stabilities, syndication, contagion, interconnectedness, etc. (Billio et al., 2012; Cai et al., 2018; Chen et al., 2016; de Bandt & Hartman, 2000; Giudici & Parisi, 2018); where the interbank network is one of main cause of the systemic risk due to financial shortage. This interbank network exists due to the financial obligations between banks where its value is determined by the claim of a bank to each other (Eisenberg & Noe, 2001). This network also exists indirectly through financial market when a bank's asset decreases significantly hence decreasing the bank's liquidity.

Hansen (2014) proposes three main factors to increase the financial systemic risk: (1) bank run due to liquidity problem, (2) financial network fragility due to contagion effect, and (3) the risk of the major banks to default. In addition, the general factors like the economic shock and institutional failure—to provide prudential regulations—will only result in an economic crisis (Schwarcz, 2008). However, contagious might not be avoided though the regulators have provided a thorough prudential regulations to enhance financial institutions' resilience (Filippopoulou et al., 2020; Jin & De Simone, 2020). In this case, technological development in the financial system and in the market have been found to increase the systemic risk (Cifuentes et al., 2005; Magnuson, 2018).

We, therefore, try to address the contagion channel that potentially increases the systemic risk through the interbank market to help understand the systemic risk management. We follow Chen et al.'s (2016) model that incorporates the network channel (interbank network) and the liquidity channel (asset market) to identify how both network multiplier and liquidity amplifier determine the probability of the systemic risk. We adopt and test the intuitive optimal strategy of Chen et al.'s model—which we will explain in the next section—using a laboratory experiment. We use students and bankers as our subjects to see how close they are to Chen et al.'s optimal strategy and to see both groups differ behaviorally in order to avoid the failure.

2 Model of financial systemic risk

Chen et al.'s (2016) model shows that a bank failure will be contagious within the financial network and that causes other banks to fail subsequently. The model assumes a financial system which consists of I banks $\{i=1, \dots, I\}$ to make an interaction in T periods $\{t=1, \dots, T\}$. This interbank interaction is assumed to be limited only on the loans and liabilities, and each bank i has assets, liabilities and equity in the balance sheet as shown in Table 1.

Table 1 Bank’s balance sheet

Assets	Liabilities and owner equity
External investments (β_i)	External debt claim (b_i)
Interbank loans ($L_{ji}; j \neq i$)	Interbank liabilities ($L_{ij}; j \neq i$)
Liquid securities (\bar{y}_i); <i>no short sale</i>	Equity (e_i)
Illiquid assets (\bar{s}_i); <i>fixed allocation</i>	

Chen et al. (2016) assume that there is no *cash* in the balance sheet (Assets). This will be impractical in our experiment since there is an interbank interaction during trading where all banks are allowed to borrow funds from others. Therefore, each bank will have a *cash* in its balance sheet (in Assets) for unallocated funds in the experiment

Where $j \neq i = \{1, \dots, I\}$ and L_{ji} , L_{ij} , b_i , and y_i have their own interest. The second assumption is ‘equal seniority’ where both L_{ij} and b_i have the same maturity. The bank is expected to make a clearing repayment (*limited liability*, x_i) through the returns of any investments on the assets. This is defined as¹:

$$x_i = \ell_i \left(\beta_i + y_i + \sum_{j \neq i} x_j p_{ji} + s_i q \right), \tag{1}$$

where ℓ_i is the total liabilities of bank i , $\left(\beta_i + y_i + \sum_{j \neq i} x_j p_{ji} + s_i q \right)$ is the total assets available in bank i , p_{ji} is the relative liabilities of bank i to other banks (j) within the same network, and q is an equilibrium price of the illiquid assets needed to be sold (s). The third assumption is that \bar{y}_i and \bar{s}_i are convertible into cash given their respective face value and equilibrium price $q = \exp(-\sum s_i)$ —with s_i is the amount of illiquid assets needed to be sold to repay the liabilities.² Given this, $0 < q < 1$ and that the q is an exogenous where the value is determined by the total of illiquid assets sold.

Following the assumptions above, a bank uses the liquid assets to repay its liabilities (revenues from external investments, interbank loans and liquid securities). A bank will sell its illiquid assets if it exhausts all of its liquid assets—given the equilibrium price q —to repay its liabilities.

$$y_i = \bar{y}_i \wedge d_i^1 := \left[\ell_i - \left(\beta_i + \sum_{j \neq i} x_j p_{ji} \right) \right]^+ \tag{2}$$

$$s_i = \bar{s}_i \wedge d_i^2 := \frac{\left[\ell_i - \left(\beta_i + \sum_{j \neq i} x_j p_{ji} \right) - y_i \right]^+}{q},$$

¹ All liabilities ℓ_i are from external debts and interbank loans.

² Both liquid and illiquid assets are assumed to be convertible without transaction costs. In addition, there is no short sale for liquid securities.

where \bar{y}_i and \bar{s}_i are the amount of liquid and illiquid assets needed to be sold for liabilities repayment—with a priority of liquid securities than the illiquid ones. The amount of s_i needed to be sold is given the q ; the higher is the q the lower is the s_i needed to be sold.

Given the definition above, a bank failure in its external investments leads to a systemic risk following a decrease in the clearing repayment (x). Therefore, the bank’s objective is to maximize the x given the external investment risk and other banks’ failure within the same network in each period t .³ Equation (1) divides the banks into: (1) default banks ($D = \{i, x_i < \ell_i\}$) and (2) non-default banks ($N = \{i, x_i = \ell_i\}$) to develop a probabilistic model assuming $D = \bar{A}$, $N = \{1, \dots, I\}$ in $t = 1$. The bank’s objective function, by identifying $\{D, N\}$, is defined as:

$$\max_{D, N, x_D, y_N, s_N} |x| \quad s.t. \quad \begin{aligned} x_D &= \beta_D + y_D + s_D q + x_D P_D + x_N P_{N,D} \\ x_N &\leq \beta_N + y_N + s_N q + x_D P_{D,N} + x_N P_N \end{aligned} \quad (3)$$

where P is a matrix of $p_{ij} := \frac{L_{ij}}{l_i}$ of both default and non-default banks; $\begin{pmatrix} P_D & P_{D,N} \\ P_{N,D} & P_N \end{pmatrix}$, $P := p_{ij}$. The constraint in the first part of Eq. (3) is the *accounting identity* that the default banks should comply with; and the second part is the *surplus constraint* where the non-default banks have to stay healthy. Equations (1)–(3) imply that the bank should have sufficient funds to avoid a failure which leads to a systemic risk caused by the contagion effect. In addition, all banks are assumed to have *liabilities* and *equity* that can be allocated in to external investment, interbank loans, liquid asset and illiquid asset in $t = 1$.

Let us take an example of Bank 1 where its external investment (b_1) does not return as expected, therefore $b_1 - Y_1 (Y_1 \hat{I}[0, b_1])$.⁴ Bank 1 in $t = 2$ will have available funds of $(\beta_1 - Y_1 + \bar{y}_1 + \sum_{j=1}^I \ell_j p_{j1} + s_1^1 q^1 < \ell_1)$ which means that Bank 1 is lack of funds to repay the liabilities. This will reduce other banks’ revenue and, simultaneously, affecting their clearing repayment and, finally, increasing the probability of the systemic risk in the network. Proposition 1 of Chen et al. (2016) shows what a bank will have if it does not make a financial interaction. In this case, the probability of Bank 1 (as an example) to fail is: $\Pr(\text{Bank 1 defaults}) \geq \Pr(Y_1 > e_1^t)$ which means that the bank’s probability of failure is derived from external investment and that does not affect other banks in the network. This proposition leads to Theorem 2 of Chen et al. (2016) of the contagion effect due to the shock of a bank (i.e. Bank 1) if it makes a financial interaction with other banks in the same network:

$$\Pr(\text{Bank } j \text{ defaults} | \text{Bank 1 defaults}) \geq \Pr\left(Y_1 > e_1^t + \frac{1}{z_{1j}} \sum_{i=2}^I e_i^t z_{ij}\right); j \neq 1, \quad (4)$$

³ The external investment risk and other banks’ failure are simultaneously affecting the systemic risk though both have different measures to affect the probability of the shock.

⁴ Y_1 is the revenue realization of the external investment of Bank 1.

where $z_{ij} = (I - P)^{-1}$ and $e_1^t + \frac{1}{z_{1j}} \sum_{i=2}^I e_i^t z_{ij}$ is the bank j 's resilience index when Bank 1 experiences shock. Equation (4) also implies the probability of other banks to fail because of Bank 1's shock.⁵ Proposition 1 and Theorem 2 underlie Chen et al.'s model where the contagion effect leads to the financial systemic risk. Given this, there are two intuitive optimal strategies for a bank to avoid a failure: (1) *imposing a higher interest of the external investment than its risk*, (2) *avoiding the financial interactions with the high-risky banks in the network*. The first strategy is to avoid the failure through liquidity channel when the external investment is endogenous in the balance sheet. The risk of the external investment is unknown and it depends on the business cycle. The second strategy is to avoid the failure through the network channel in which it is a function of other banks' clearing repayment; which is also caused by the external investment shock. The bigger is the shock from both channels, the higher is the financial systemic risk in the network. This paper tries to check the validity of Chen et al.'s (2016) intuitive optimal strategies following its setup as appropriate in the laboratory experiment.

3 Experimental design

We involve 72 students from Universitas Gadjah Mada and 32 bankers from 26 rural banks in Yogyakarta, Indonesia in this experiment. All subjects were invited through e-mail with an official letter from Indonesia Deposito Insurance Corporation (IDIC). The educational background (on-going for student and completed for bankers) are: 11% are diploma, 86% are undergraduate and 3% are master within the student group; 10% are senior high school, 6% are diploma, 71% are undergraduate and 13% are master within the banker group.

Due to Covid-19 pandemic, we use an online lab experiment with subjects were in the video call meeting all at the same time; we also asked them to turn on their PC/laptop camera during the experiment. All subjects were divided into a group of four which refers to the bank's network; and we separate sessions between students and bankers. We distributed the Instructions and read it aloud before the session was started to make sure the subjects understand what they are asked to do and making clear of all questions. We also checked their internet connection before subjects completing a practice session and the real experiment.⁶ This was preceded by a pilot experiment (with eight students) but we do not report the results here.⁷

Subjects play five rounds with each round consisting of T periods. They can only interact each other within their group during T periods, however, we limit up to seven periods in each round for the time reason. We randomize the composition of the group in each round and the round order in each session to avoid the order effect;

⁵ This failure will possibly cause a failure in external debts repayment.

⁶ We asked subjects to check their internet connection through *speedtest.com* and to report us at the beginning of the session.

⁷ This is to check if the software works properly without unnecessary bugs and to see if the subjects understand what they were being asked to do.

subjects were not told the personal information of other subjects in the same group. The number of periods (T) in each round is determined by a virtual die roll following these procedures: (1) a die is rolled after subjects complete one period, (2) if a die shows 1 then the round is over, (3) if a die shows 2–6 then the round is still going on up to seven periods.⁸ Subjects were given their financial performance in each round by the end of a particular round which is measured by the difference between the final equity (e_T) and the initial equity ($e_1 = 1$).⁹ By this we induce the subject to be a bank manager that manages the bank's financial stability and to increase the bank's size.

We employ Stecher et al. (2011) to generate ambiguous numbers to be used in several treatments.¹⁰ This is to represent the uncertainty situation in this experiment without violating the assumptions of the theory.¹¹ First, a subject will have a total asset (V) which consists of external debts (b) and equity (e) at $t=1$. The value of V is ambiguous by taking a number between 1000 and 10,000 without a subject knowing of other's total asset. The value of e is between 12 and 20% (which is generated ambiguously as explained) of the V ; hence the value of $b = V - e$. We assume that b needs to be repaid by the end of every period with an interest v which varies in every round—so v is fixed in all periods within a particular round. The value of e is determined in the beginning of every round and it will be a basis of a subject's performance in that particular round.

In the next period, we use the ambiguous distribution to determine b when the subject receives the external debts at $t+1$. The value of b_{t+1} is always between 80 and 120% of the b_t to represent the different capacity of each bank to absorb external funds. The V can be allocated into four components of Assets as in Table 1. We put a priority of this allocation in to illiquid asset (\bar{s}_i) which is the bank's last resort for clearing repayment. We arbitrarily impose the \bar{s}_i to be between 8 and 12% and it, again, is determined ambiguously. The illiquid asset price (q) at $t=1$ is always 1, and that we adjust the $q = \exp \left[- \sum \left(\frac{s_j}{1000} \right) \right]$ in order to have variabilities in q . The value of q is determined by the market equilibrium given the amount of s needed to be sold by any bank in the group at $t > 1$; the higher is the amount of s sold by any bank, the lower is the q . A subject can sell its s automatically up to \bar{s}_i in order to clear its repayment in any period.

The next priority for Asset allocation is on a set of external investment (b_i), inter-bank loans ($L_{ji}; j \neq i$) and liquid securities (y)—subject can allocate as they like on these with a maximum of $V - \bar{s}_i$. Chen et al. (2016) assume that b_i and L_{ji} are fully absorbed by the market for given interests. However, there will be two consequences

⁸ Given this, the probability of a round to finish before seven periods is 1/6.

⁹ The final equity (e_T) is the equity value by the end of a round, and the initial equity ($e_{t=1}$) is the given value—from a randomization process—at the beginning of a round.

¹⁰ This will refer to ambiguous distribution to be used in the ambiguous situation throughout this paper.

¹¹ Chen et al. (2016) do not specify the distribution of each component in the balance sheet or the risk of each investment. However, they state that each bank may have different size and its risk to each other. Neither experimenters nor the subjects have knowledge of this ambiguity distribution other than the specified boundaries in each treatment.

in this experiment. First is a behavioral consequence where subject will always impose a high interest on both b_i and L_{ji} (for any given risks) due to a sure absorption on both. Second is a technical consequence where each bank has to absorb the interbank loans allocation which is impractical in the experiment.

We therefore arbitrarily apply some rules in the experiment without loss of generalization on Chen et al.'s assumptions. First rule applies on the mean of external investment absorption (PE) which is a function of the interest rate (EI_{int}). The rules are as follows:

- a. If $EI_{int} \leq 11\%$ then PE is 100% of subject's allocation.
- b. If $EI_{int} > 11\%$ then PE drops by 1% for every 0.5% of an increase on r .
- c. Following (a) and (b), the realization of external investment absorption (RPE) is determined randomly using normal distribution with mean of PE and standard deviation of 3%.
- d. If the random number shows more than 100% then $RPE = 100\%$; if the random draw shows less than 0% then $RPE = 0\%$.

Following the rules above, there will be unallocated funds if $0\% \leq RPE < 100\%$. Therefore, we add 'Cash' (C) in Assets side—this is automatically added (Table 2).

We involve a risk in the external investment (EI_{risk}) which is determined randomly using Pearson distribution with mean of 7%, standard deviation of 5%, skewness of 1% and kurtosis of 4% (right skewed). Given this, the realization of EI_{risk} is, theoretically, between $-\infty$ and ∞ , hence we apply the following rules: $EI_{risk} = 0\%$ if the random number is negative, $EI_{risk} = 100\%$ if the random number is more than 100%.¹²

Subject is free to allocate L_{ji} and its interest rate (m). The realization of L_{ji} is determined by the interaction between subjects during trading session. The unallocated funds from this trading will be added automatically in to C at $t+1$. However, no information of other subjects' balance sheet for each subject. The last allocation is on the liquid securities (\bar{s}_i) which is risk-free with a fixed return. We assume that its face value is always 1 across periods, though its return varies between rounds. Subject will be made inactive in a particular round (unable to make any financial activities) if he/she cannot make a clear repayment to their liabilities in any period of a particular round. As a consequence, the value of illiquid asset (\bar{s}_i) is known at the beginning of the new period ($t+1$) given the recording process of the financial transactions, hence the information of failure can only be generated at $t+1$.¹³

We, once again, impose a rule for this case in which the remaining asset—of the failed subject—will be proportionally allocated to other subjects who owe interbank loans to the failed bank.¹⁴ However this failed subject will only follow the rounds without making any financial activities. All subject's financial activity is made in

¹² However, our simulations result in random numbers with a least number of (about) 0.8 and a highest number of (about) 49. The details are in the Instructions.

¹³ A subject may fail during period t , but the information of this failure will be shown at $t+1$ after all financial transactions have been recorded and calculated depending upon the illiquid asset value.

¹⁴ This includes the case when a particular round has finished.

Table 2 Subject's balance sheet in the experiment

Assets	Liabilities and owner equity
Cash (C_i)	External debt claim (b_i)
External investments (β_i)	Interbank liabilities ($L_{ij}; j \neq i$)
Interbank loans ($L_{ji}; j \neq i$)	Equity (e_i)
Liquid securities (\bar{y}_i); <i>no short sale</i>	
Illiquid assets (\bar{s}_i); <i>fixed allocation</i>	

Table 3 External debt interest and liquid securities return used in the experiment

Round	Sequence	External debt interest (%)	Liquid securities return
1	Lower 1:1	1	1
2	Lower 1:2	1	2
3	Middle 1:2	2	4
4	Upper 1:2	3	6
5	Upper 1:1	5	5

We randomly order the scenario in the experiment

every period to satisfy the assumption of ‘equal seniority’ for clearing repayment. Lastly, we arbitrarily set five combinations of hypothetical parameters on external debt interest and liquid securities return by ratio—1:1 and 1:2 (Table 3).

All subjects will face two main interfaces as shown in Instructions (Online Appendix 2). *First* is the information of the subject's balance sheet which consists of total assets (V), liabilities (L_{ij} and b) and equity (e). Subject can allocate V on the external investment (β), interbank loans ($L_{ji}; j \neq i$) and liquid securities (\bar{y}) as they like after random allocation of illiquid assets (\bar{s}). The remaining V is automatically allocated in cash (C) and will be carried on in the next period—with the value depends upon the liabilities. This is the first stage of the experiment where the subject has to make the necessary allocation as their decision. Subject has 2 min to make his/her allocation and the respective interest rates before going on to the second stage (*Panel b*). We impose zero allocation if subject does not make an allocation in the first stage.

Second is for banks interaction given each bank allocation on the interbank loans and its interest in the first stage; this will refer to the second stage where the subject interacts with other subjects. The left side of *Panel b* (in the Instructions) shows the realization of the external investment risk, external investment revenue, interbank loans, liabilities and total assets; the right side of *Panel (b)* shows the availability of funds to borrow in the market and the loan box. Subject can make a loan by inputting a number to the respective subject depending upon the fund availability. All information in this stage is real time following the financial activities between

banks. Subjects are also told if there is a failed subject in this Panel.¹⁵ This second stage lasts for 3 min and that we impose zero loans if a subject does not make any loans to the respective subject. Our experiment will have a two-stage decision: the determination of financial allocation in the first stage and financial interactions between subjects in the second stage.

Monetary incentives are provided for the subjects to reveal their true preferences. We use a random incentive mechanism to determine the subject's payment by taking one round (out of five in the main experiment). Given this, the subject's payment from a particular round is the difference between the final equity and the initial equity which means the subject successfully manages the bank towards its objectives. This is added with a show-up fee of IDR20,000 and the total payment is: $IDR20,000 + 20(e_T - e_1)^+$.¹⁶

4 Results and analyses

We start the analyses by identifying the percentage of banks to have failed in each period in the particular round.

Figure 1 shows a significant increase in both groups as the period continues, especially in Round 5 (5% external debt interest and 5% liquid securities return). Overall, there are 190 failures (10.58%) in all periods and rounds within student group; and 47 failures (7.08%) within banker group. The lowest percentage of failed banks occur in Round 2 (1% external debt interest and 2% liquid securities return) in both groups. This shows that sequence 'upper 1:1' tends to bring a failure, therefore leads to a systemic risk; otherwise for sequence 'lower 1:2'.

4.1 The determination of external investment interest

One basic optimal strategy of Chen et al. (2016) for a bank to avoid failure is to impose the external investment interest (EI_{int}) above its risk (EI_{risk}). We analyze this using non-failed banks in all periods and rounds: with a total of 1675 observations within student group and 617 observations within banker group. The average EI_{int} in all rounds are 7.5% (student group) and 7.43% (banker group); with the average $EI_{int} - EI_{risk}$ are 0.49% (student group) and 0.59% (banker group). These findings indicate that the subjects, in general, follow the optimal strategy of Chen et al. (2016)—imposing EI_{int} above EI_{risk} —though they are not told EI_{risk} when they impose EI_{int} . This also shows that the source of bank failure is not from the external investment shock.

¹⁵ Subjects do a practice session of two periods. However, we let the subjects to have more than one practice session if they were asking for that.

¹⁶ We pay the subjects using online payment as a part of social distancing during Covid-19 pandemic. USD equals about IDR14,000 at the time of the experiment.

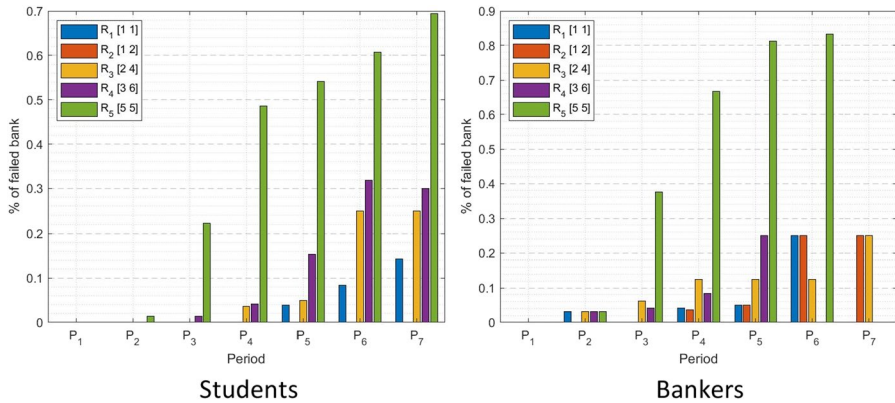


Fig. 1 Percentage of failed banks in each period

We then delve deeper in the analysis of EI_{int} vs EI_{risk} in each round as shown in Fig. 2. The average subjects’ $EI_{int} - EI_{risk}$ is positive in each round, except Round 4, for both groups. Given this, subjects successfully avoid the failure from external investment shock; though low profit made from this external investment (around 0.5% for both groups).

Table 4 identifies if subjects determine EI_{int} and understand the distribution of EI_{risk} differently; they are told the distribution and simulation of EI_{risk} in the Instructions. Both Wilcoxon signed-rank and Kruskal–Wallis tests show that only Round 4 sees student group have a different perception in determining EI_{int} and understanding the distribution EI_{risk} . This indicates that, in general, subjects determine EI_{int} based on their understanding on the distribution of EI_{risk} —though EI_{risk} is randomly distributed.

Next is the regression analysis on subjects’ determination of EI_{int} . We use Tobit regression for estimation and the results are as follows¹⁷:

$$\begin{aligned} \widehat{EI}_{int}^M &= 11.425 + 0.02EI_{risk}^M - 0.043\ln TA^M - 0.426ED_{int}^M \\ &\quad (5.465)^{**} \quad (0.049) \quad (0.601) \quad (0.157)^* \\ &\quad - 2.199Gender^M + 0.305Age^M - 2.797Educ^M \\ &\quad (0.523)^* \quad (0.113)^* \quad (0.722)^* \\ \widehat{EI}_{int}^B &= -13.088 + 0.023EI_{risk}^B + 1.435 \ln TA^B \\ &\quad (6.95)^{***} \quad (0.063) \quad (0.747)^{***} \\ &\quad + 0.358 ED_{int}^B - 0.509Gender^B - 0.279Age^B \\ &\quad (0.191)^{***} \quad (0.709) \quad (0.084)^* \\ &\quad + 4.649Educ^B - 1.111Pos^B + 0.472Exp^B \\ &\quad (0.587)^* \quad (0.743) \quad (0.105)^* \end{aligned}$$

¹⁷ See Qian (2009) for the Tobit model that we use here. The total observation is 1675 within student group and 617 observations within banker group. (*, **, ***) indicate a significant level at 1%, 5% and 10% respectively, and standard errors are in parenthesis.

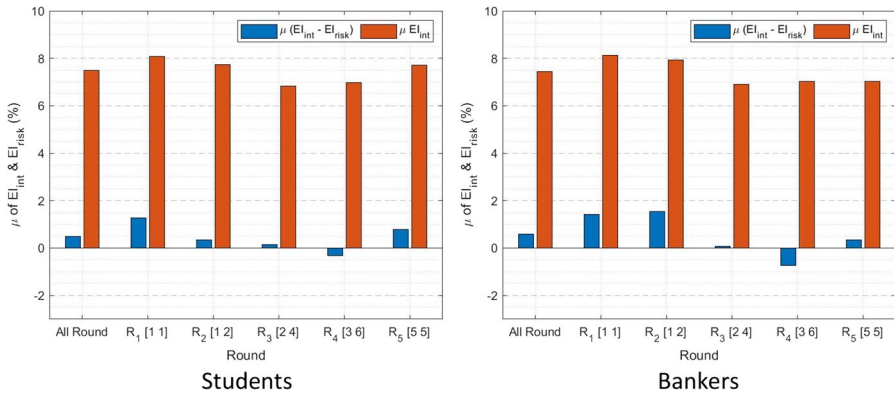


Fig. 2 EI_{int} vs EI_{risk}

Table 4 Wilcoxon signed-rank and Kruskal–Wallis test for EI_{int} and EI_{risk}

Round (sequence)	Students		Bankers	
	Sum-rank Z-value	Kruskal–Wallis χ^2	Sum-rank Z-value	Kruskal–Wallis χ^2
All rounds	-1.993	3.971	0.326	0.107
Lower 1:1	0.784	0.616	0.829	0.689
Lower 1:2	-1.888	3.565	1.004	1.009
Middle 1:2	-0.433	0.188	-0.693	0.482
Upper 1:2	-2.688*	7.225*	-0.861	0.741
Upper 1:1	-0.359	0.129	0.329	0.109

*Indicates a significance at 1%

where TA is total asset, ED_{int} is the external debt interest, M is student subjects, B is banker subjects, and a set of control variables: $Gender$ is subject’s gender (0= male, 1= female), Age is subject’s age, $Educ$ is subject’s educational background, Pos is banker’s position level (0=staff, 1=manager) and Exp is banker’s experience in banking/financial industry (in years). The estimation shows a different behavior between *student* and *banker* groups in the determination of EI_{int} : TA and ED_{int} are significant determinants to EI_{int} in the banker group, but only ED_{int} is significant determinant to EI_{int} in the student group. However, both groups are found not to use EI_{risk} in the determination of EI_{int} —which is a part of the optimal strategy—though they have a similar perception in determining EI_{int} and understanding the distribution EI_{risk} . In addition, both groups exhibit a different behavior on the sign of Age and $Educ$ background as the significant determinants of EI_{int} .

4.2 Interbank interactions

The interbank interactions, in our context, occur when the allocation of interbank loans (AIB_{loans}) is absorbed in the market (by other banks in the same group). The absorbed AIB_{loans} will be a realization of interbank loans in the current period and will increase the bank's revenue by the end of period. The other banks to make this loan will increase its cash which can be allocated in to productive assets and become interbank liabilities (IB_{liab}) to be repaid by the end of period. Therefore, a bank will maximize the AIB_{loans} interest to maximize its profit, whereas the debtors (other banks) will maximize their choice by making their interbank loans with the least interest. Figure 3 shows the realization of interbank loans (IB_{loans}) and its interest (iIB_{loans}).

The average of IB_{loans} realization within student group is $\pm 30\%$ and within banker group is $\pm 37\%$; and the highest average of IB_{loans} realization occurs in Round 3 for both groups.¹⁸ However, both groups exhibit a different lowest average of IB_{loans} realization: Round 1 within student group and Round 5 within banker group. The average iIB_{loans} is 3.8% within student group and 6.5% within banker group. Both groups are found to have a negative correlation between IB_{loans} realization and iIB_{loans} (-0.043 within student group and -0.059 within banker group) which is unsurprisingly if subjects are to maximize their profit.¹⁹

Following Chen et al. (2016), one failure will increase the chance/possibility of other banks to fail to repay their IB_{liab} ; hence decreasing the revenue and limited liability. Though it is best for a bank to avoid lending to the risky bank, subjects in our experiment cannot specifically to whom they will lend the money, nor that they can observe the probability of a bank to fail. However, they can observe their illiquid asset values (IA_{value}) in every period: a decreasing IA_{value} indicates a chance of systemic risk in the network/group in which there is a bank to sell their illiquid asset (s).

Figures 4 and 5 show a positive correlation between AIB_{loans} and IA_{value} in both student and banker groups respectively. However only in the student group to show a positive correlation between AIB_{loans} and IB_{liab} . We then delve deeper with a linear regression model to estimate the determinants of AIB_{loans} for both groups.²⁰ Our main concern is to explore if a decrease in illiquid asset is significant to the determination of AIB_{loans} .

¹⁸ Only subjects to allocate the IB_{loans} are sampled.

¹⁹ In this case, the banker group is more sensitive in the absorption of IB_{loans} than that of the student group.

²⁰ We use linear regression model for estimation. The total observation is 1675 with adj-R² of 0.013 within student group; whereas the total observation is 617 with adj-R² of 0.153 within banker group. (*, **, ***) indicate a significant level at 1%, 5% and 10% respectively, and standard errors are in parenthesis.

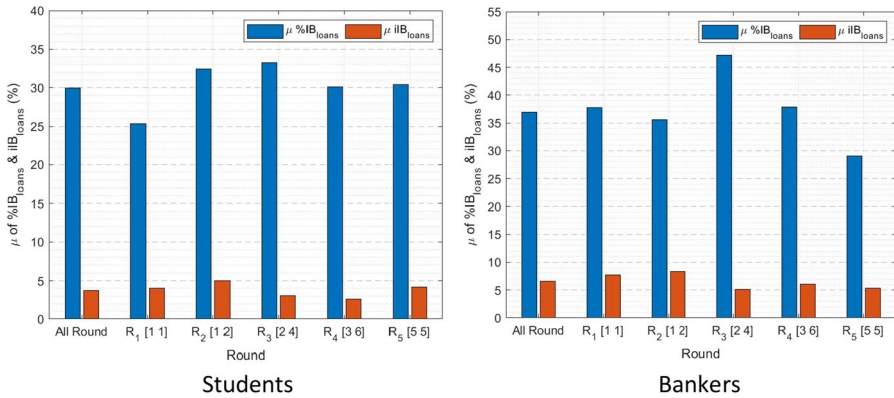


Fig. 3 Percentage of IB_{loans} realization and iIB_{loans}

$$\begin{aligned} \ln \widehat{AIB}_{loans}^M &= -13.151 - 1.74 \text{ DATL}^M + 0.424 \ln TA^M \\ &\quad (6.202)^{**} \quad (0.677)^* \quad (0.683) \\ &\quad + 0.142 \ln IB_{liab}^M + 1.409 \text{ Gender}^M \\ &\quad (0.02)^* \quad (0.589)^{**} \\ &\quad + 0.195 \text{ Age}^M + 1.978 \text{ Educ}^M \\ &\quad (0.129) \quad (0.814)^{**} \end{aligned}$$

$$\begin{aligned} \ln \widehat{AIB}_{loans}^B &= 11.317 + 1.898 \text{ DATL}^B + 1.655 \ln TA^B \\ &\quad (10.182) \quad (1.016)^{***} \quad (1.119) \\ &\quad + 0.01 \ln IB_{liab}^B + 1.287 \text{ Gender}^B \\ &\quad (0.033) \quad (1.079) \\ &\quad - 1.007 \text{ Age}^B + 1.359 \text{ Educ}^B \\ &\quad (0.116)^* \quad (0.813)^{***} \\ &\quad + 0.817 \text{ Exp}^B - 1.195 \text{ Pos}^B, \\ &\quad (0.15)^* \quad (1.097) \end{aligned}$$

where $DATL$ is a dummy variable if there is a decrease in illiquid asset. The estimation shows a different behavior between student and banker groups: an occurrence of a decrease in illiquid asset decreases AIB_{loans} within student group, while banker group shows the opposite. Given this, we conclude that the student group follows the optimal strategy of Chen et al. (2016) where they should lower interbank interaction when there is an indication of systemic risk. A major concern might be on the banker group in which they tend to increase AIB_{loans} when there is an occurrence of a decrease in illiquid asset.

4.3 Bank’s resilience from a shock

One important measure of Chen et al. (2016) is the resilience index which is addressed to measure the bank’s resilient to avoid failure when there is a shock in the network. Interbank interactions (through loans) and equity are, theoretically, the determinants of a bank’s resilience index.

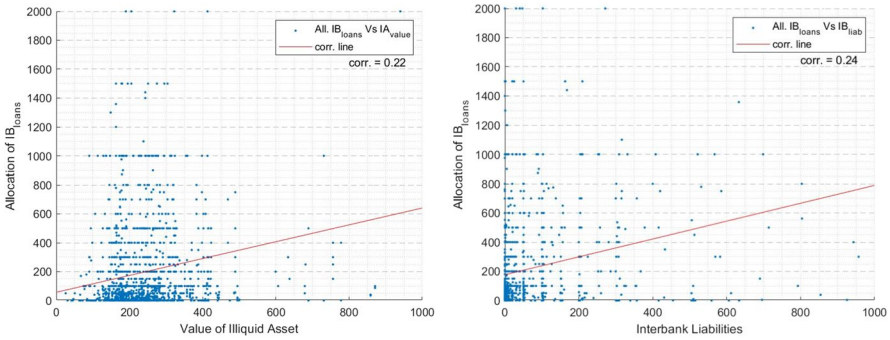


Fig. 4 AIB_{loans} vs IA_{value} and AIB_{loans} vs IB_{liab} (student group)

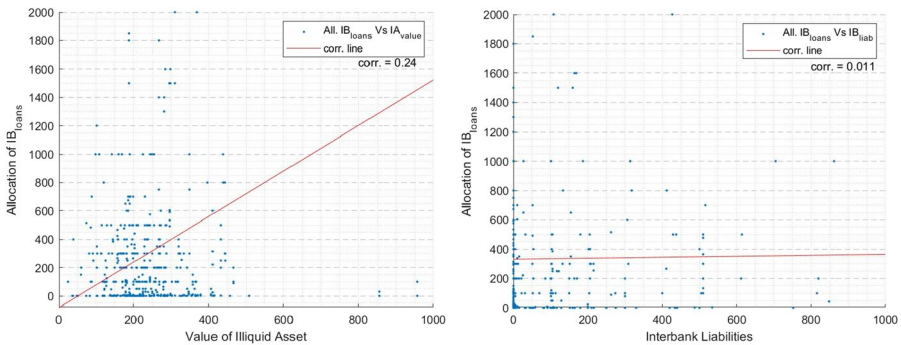


Fig. 5 AIB_{loans} vs IA_{value} and AIB_{loans} vs IB_{liab} (banker group)

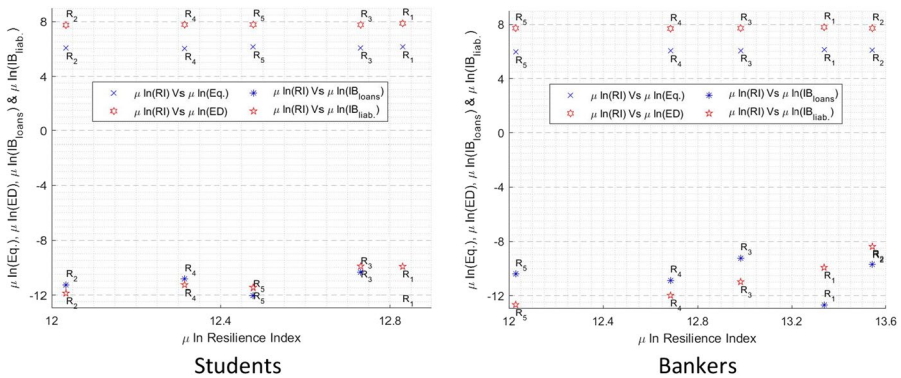


Fig. 6 Bank’s resilience index, equity and interbank loans

Figure 6 shows a plot between resilience index (RI), equity (Eq), interbank liabilities (IB_{liab}) and realization of interbank loans (IB_{Rloans}). The higher is the RI , the lower is the chance of a bank to fail due to contagion effect. There is a behavioral difference between student and banker groups where the highest average RI

of student groups occurs in Round 1 (lower 1:1); while the highest average *RI* of banker group occurs in Round 2 (lower 1:2). It also occurs with the lowest average *RI* between student group (in Round 2, lower 1:2) and banker group (in Round 5, upper 1:1). In addition, the average *RI* of banker group is always higher than that of the student group in all rounds.

We then estimate the determinants of *RI* following Theorem of Chen et al. (equity and realization of interbank loans and liabilities) added with control variables in each group.²¹

$$\begin{aligned}\widehat{\ln RI}^M &= 4.667 + 0.326 \ln Eq^M - 0.025 \ln IB_{Rloans}^M \\ &\quad (0.4)^* \quad (0.049)^* \quad (0.003)^* \\ &\quad + 0.191 \ln IB_{liab}^M - 0.026 Gender^M \\ &\quad (0.002)^* \quad (0.058) \\ &\quad + 0.014 Age^M + 0.095 Educ^M \\ &\quad (0.013) \quad (0.08)\end{aligned}$$

$$\begin{aligned}\widehat{\ln RI}^B &= 12.131 + 1.01 \ln Eq^B - 0.055 \ln IB_{Rloans}^B \\ &\quad (1.487)^* \quad (0.16)^* \quad (0.008)^* \\ &\quad + 0.458 \ln IB_{liab}^B - 0.424 Gender^B + 0.013 Age^B \\ &\quad (0.008)^* \quad (0.264) \quad (0.028) \\ &\quad - 0.52 Educ^B + 0.791 Pos^B - 0.037 Exp^B \\ &\quad (0.2)^* \quad (0.269)^* \quad (0.036)\end{aligned}$$

The estimation shows a similar result between student and banker groups where equity (a positive effect), realization of interbank loans (a negative effect) and interbank liabilities (a positive effect) are the determinants of bank's resilience index. This result also follows Chen et al.'s prediction for those three variables—given the sign of the variables—and that a bank's fundamental capacity (equity) plays an important role in order to reduce the systemic risk within the network. In addition, within the banker group, education tends to reduce the bank's resilience index—which is an unexpected result—and a managerial level subjects tend to have a higher resilience index—which is what we expect to be.

4.4 Bank's failure

The previous sub-section shows that equity plays an important role to reduce the systemic risk within the network. Given this, a bank is expected to make a profit—from any investment strategies—in order to increase its equity hence avoiding a failure which possibly be contagious (leading to a systemic risk) within the network. Our experiment induces this through equity: the higher is the equity, the higher is the payment for subjects. A bank will fail with a negative equity, therefore, we use

²¹ We use linear regression model for estimation. The total observation is 1675 with adj-R² of 0.852 within student group; whereas the total observation is 617 with adj-R² of 0.859 within banker group. (*, **, ***) indicate a significant level at 1%, 5% and 10% respectively, and standard errors are in parenthesis.

this as a probability measure of a bank's failure in each period which is given by: $\left| \frac{\Delta Eq_p}{Eq_p} \right|$ when there is a decrease in equity.

Figures 7 and 8 show a clear decreasing pattern between bank's probability to fail (PF) and revenue of external investment (EI_{rev}) and security (S_{rev}) respectively; but not with revenue of interbank loans (RIB_{loans}). In addition, there is also clear increasing pattern between bank's probability to fail and interest expenses (of external and interbank debts, $IntExp$). Although it unsurprising results, we might expect that subjects use external investment and security channels to avoid failure; and to reduce the amount of interbank loans. We then estimate the determinants of PF using revenue from subjects' allocations (EI_{rev} , S_{rev} and RIB_{loans}) and interest expenses ($IntExp$). We use Tobit regression to model this—added with control variables—with the results as follows²²:

$$\begin{aligned} \widehat{PF}^M &= -39.532 + 14.774 \ln IntExp^M \\ &\quad (8.85)^* \quad (1.027)^* \\ &\quad + 0.116 \ln EI_{rev}^M - 0.998 \ln S_{rev}^M \\ &\quad (0.082) \quad (0.094)^* \\ &\quad - 0.073 \ln RIB_{loans}^M - 6.735 Gender^M \\ &\quad (0.06) \quad (1.735)^* \\ &\quad + 0.065 Age^M - 5.509 Educ^M \\ &\quad (0.361) \quad (2.299)^{**} \end{aligned}$$

$$\begin{aligned} \widehat{PF}^B &= 2.21 + 16.012 \ln IntExp^B - 1.17 \ln EI_{rev}^B - 0.115 \ln S_{rev}^B \\ &\quad (15.629) \quad (1.716)^* \quad (0.185)^* \quad (0.155) \\ &\quad + 0.086 \ln RIB_{loans}^B + 2.501 Gender^B - 1.484 Age^B \\ &\quad (0.115) \quad (3.159) \quad (0.387)^* \\ &\quad - 2.636 Educ^B - 12.436 Pos^B + 1.789 Exp^B \\ &\quad (2.538) \quad (3.381)^* \quad (0.51)^* \end{aligned}$$

The estimation above shows that interest expenses (of external and interbank debts) are significant to increase the bank's probability to fail in both groups; though the magnitude is slightly different between them. However, there is a different allocation strategy between both groups to avoid a failure: student group uses security channel while banker group uses external investment channel. An important note of these results is that only one channel to appear significant to reduce PF —in each group—which, by the coefficient, does not exceed the interest expenses. This can be a further exploration on how to effectively manage the debts to increase profit and to avoid a failure.

²² See Qian (2009) for the Tobit model that we use here. The total observation is 1675 within student group and 617 observations within banker group. (*, **, ***) indicate a significant level at 1%, 5% and 10% respectively, and standard errors are in parenthesis.

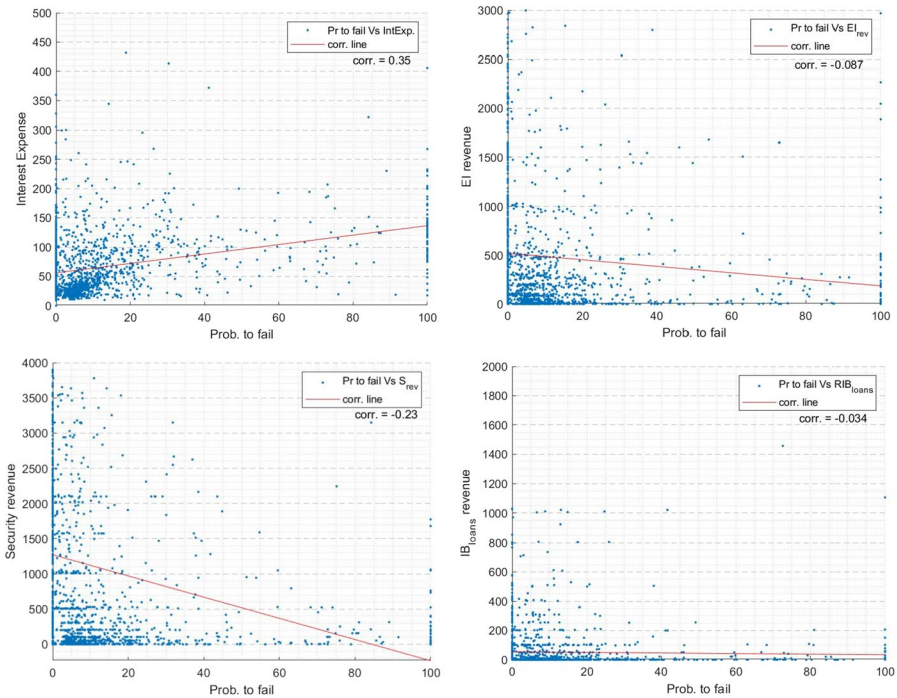


Fig. 7 Bank's probability to fail vs equity, external investment revenue, interbank loans revenue and security revenue within student group

5 Discussion and conclusion

We provide an experimental investigation to check the validity of Chen et al.'s optimal intuitive strategy to avoid a systemic risk in a financial network. We use a controlled online experiment due to Covid-19 pandemic which allows us to divide our subjects into groups to make a financial interaction. There are two optimal intuitive strategies for a bank to avoid failure: (1) imposing an external investment interest higher than that of its risk, (2) avoid financial interactions with high-risk banks in the network. We use students (Universitas Gadjah Mada) and bankers (staffs at rural banks in Yogyakarta) as our subjects.

Our results show that both subject groups partially follow Chen et al.'s optimal intuitive strategies: imposing an external investment interest higher than that of its risk. However, our estimation shows that the external investment risk is not a determinant factor to the subjects' external investment interest. This should be the case that our subjects use different understanding on the distribution of the external investment risk when imposing the external investment interest. A further exploration can be made since our subjects successfully have a higher external investment interest than that of its risk, hence trying to avoid a failure from this channel, without having a connection between these two.

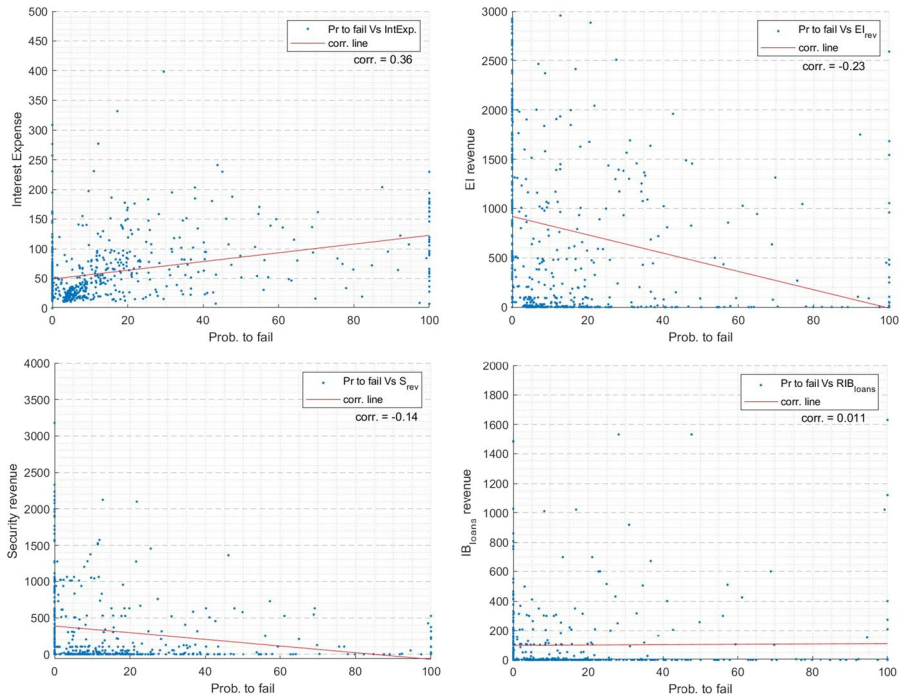


Fig. 8 Bank's probability to fail vs equity, external investment revenue, interbank loans revenue and security revenue within banker group

Only the student group is found to follow the second optimal intuitive strategy of Chen et al. where they tend to reduce the allocation of interbank loans when there is a shock possibility in the network—given the decrease on illiquid asset price. The banker group, contrary, is found to tend to increase the allocation of interbank loans when there is a shock possibility in the network. This looks irrational, however, Freixas et al. (2000) show—through modeling—that banks may increase the interbank loans to enhance the network resiliency during the shock if there is a strong financial structure within the network that maintains the banking system stability. This might be the best practice by the bankers if they assume a strong banking system in our experiment.

Next, we find that equity and interbank debts significantly increase bank's resilience index; while interbank loans significantly decrease bank's resilience index in both groups. The relationship between these three variables—equity, interbank debts and interbank loans—and bank's resilience index follows Chen et al.'s prediction (Theorem 2) where bank's resilience index is a function of equity and proportion of interbank debts (made by other banks) to the bank's total liabilities. This explains how the bank's resilience will be low if other banks experience a shock while having interbank debts to the respective bank. However, the interbank loans will increase other banks' resilience index, hence, reducing the systemic risk in the network. This

may explain the behavior of banker subjects in the previous section though further exploration is needed.

Lastly, we find that both subject groups have a different behavior in avoiding failure where students use the security channel (holding more securities) while bankers use external investment channel (increasing external investment allocation). Although every bank (or every network) is free to use every available channel, this maps the banks' behavior under some circumstances and backgrounds to maximize their profits; though there is no different treatment between two groups. One could possibly argue that the difference is due to the different sample in which bankers are considered to be more risk taking than that of students due to their experiences in the banking industry; allocating in to the risky external investment than in to riskless security. A study from Gärling et al. (2020) shows, using a lab experiment, that more educated subjects tend to be more confident in taking the risky financial assets though it has no significant association with the chance of profit making.

We are fully aware that there might be potential biases in this study, however we have tackled the issues. First, network channel might not occur if the subjects do not allocate interbank loans, especially when they find changes in illiquid assets in the later periods, and that we could not force them to do so. Nevertheless, the systemic risk might still occur even if the subject did not allocate the interbank loans due to the changes in illiquid assets; it might change if other banks have shortfall or fail. Second, we induce the subjects to maximize their payment to maintain their performance in this experiment. Third, the default is merely due to the financial activities (i.e. losses from external investments, losses from interbank loans, and changes in illiquid assets) although the subject has made the optimal decisions.

Besides checking the empirical validity of Chen et al. (2016), we also contribute to the literature on the exploration of the individual behavior—as a bank manager—in the financial network. This serves as an alternative in identifying the source of systemic risk; see Benoit et al. (2017) for a survey on the exploration of systemic risk sources. The behavior of bank managers in allocating assets might contribute a necessary role in the sources of systemic risk stemming from systemic risk-taking and contagion. We identify some different personal attributes to determine four important interests in our study: (1) external investment interest, (2) allocation of interbank loans, (3) bank's resilience index, (4) failure avoidance. The ideal further studies should be on the managerial capabilities to manage the internal risk for lending purpose and banking system stability, as well as the effectiveness of relevant interventions to lower the systemic risk.

Supplementary Information The online version contains supplementary material available at <https://doi.org/10.1007/s40822-022-00207-7>.

Acknowledgements This research receives financial support from Indonesia Deposit Insurance Corporation through 'LPS Call for Proposal 2019/2020' grant scheme. We thank Ade Chrisnadhhi for his enormous helps in writing the experimental interface. We also thank to two anonymous referees and participants at 36th EBES Conference for helpful comments. Results and findings of this research do not represent Indonesia Deposit Insurance Corporation view. We declare that we have no competing interest with other parties. All errors and omissions are solely ours.

Author contributions YP: conceptualisation, methodology, data collection, formal analysis, writing. SA: conceptualisation, software, formal analysis, writing, review. AN: data collection, review, project administration.

Funding We receive financial support from Indonesia Deposit Insurance Corporation (IDIC) through ‘LPS Call for Proposal 2019/2020’ grant scheme (PKS-4/GRIS/2019).

Availability of data and material All data and materials are available upon request to the corresponding author.

Declarations

Conflict of interest We confirm that we are not part of Indonesia Deposit Insurance Corporation (IDIC). Results and findings from this research do not represent IDIC view.

Code availability All codes are available upon request to the corresponding author.

Consent to participate It is provided prior to the experiment. The details of this consent to participate is in the Online Appendix. A subject has to sign the consent to participate before participating in this experiment.

References

- Acharya, V., Pedersen, L., Philippon, T., & Richardson, M. (2017). Measuring systemic risk. *The Review of Financial Studies*, *30*(1), 2–47.
- Benoit, S., Colliard, J.-E., Hurlin, C., & Perignon, C. (2017). Where the risks lie: A survey on systematic risk. *Review of Finance*, *21*(1), 109–152.
- Billio, M., Getmansky, M., Lo, A., & Pelizzon, L. (2012). Econometrics measures of connectedness and systemic risk in the finance and insurance sectors. *Journal of Financial Economics*, *104*(2012), 535–559.
- Cai, J., Eidam, F., Saunders, A., & Steffen, S. (2018). Syndication, interconnectedness, and systemic risk. *Journal of Financial Stability*, *34*, 105–120.
- Chen, N., Liu, X., & Yao, D. D. (2016). An optimization view of financial systemic risk modeling: Network effect and market liquidity effect. *Operations Research*, *64*(5), 1089–1108.
- Cifuentes, R., Ferrucci, G., & Shin, H. S. (2005). Liquidity risk and contagion. *Journal of the European Economic Association*, *3*(2/3), 556–566.
- de Bandt, O., & Hartmann, P. (2000). *Systemic risk: A survey*. European Central Bank working paper no. 35.
- Eisenberg, L., & Noe, T. (2001). Systemic risk in financial systems. *Management Science*, *47*(2), 236–249.
- Filippopoulou, C., Galarotis, E., & Spyrou, S. (2020). An early warning system for predicting systemic banking crises in the Eurozone: A logit regression approach. *Journal of Economic Behavior and Organization*, *172*, 344–363.
- Freixas, X., Parigi, B. M., & Rochet, J. C. (2000). Systemic risk, interbank relations, and liquidity provision by the central bank. *Journal of Money, Credit & Banking*, *32*(3), 611.
- Gärling, T., Fang, D., & Holmen, M. (2020). Financial risk-taking related to individual risk preference, social comparison and competition. *Review of Behavioral Finance, Online Version*. <https://doi.org/10.1108/RBF-11-2019-0153>
- Giudici, P., & Parisi, L. (2018). CoRisk: Credit risk contagion with correlation network models. *Risks*, *6*(3), 95. <https://doi.org/10.3390/risks6030095>
- Hansen, L. (2014). Challenges in identifying and measuring systemic risk. In M. Brunnermeier & A. Krishnamurthy (Eds.), *Risk topography: Systemic risk and macro modeling* (pp. 15–30). Chicago: University of Chicago Press.

- Hellwig, M. F. (2009). Systemic risk in the financial sector: An analysis of the subprime-mortgage financial crisis. *De Economist*, 157, 129–207.
- Jin, X., & De Simone, F. N. (2020). Monetary policy and systemic risk-taking in the Euro area investment fund industry: A structural factor-augmented vector autoregression analysis. *Journal of Financial Stability*, 49, 100749. <https://doi.org/10.1016/j.jfs.2020.100749>
- Magnuson, W. (2018). Regulating fintech. *Vanderbilt Law Review*, 71(4), 1167–1226.
- Qian, H. (2009). *Estimating SUR Tobit model while errors are Gaussian scale mixtures: With an application to high frequency financial data*. MPRA paper no. 31509. Retrieved from <https://mpra.ub.uni-muenchen.de/31509/>.
- Schwarcz, S. (2008). Systemic risk. *The George Town Law Journal*, 97, 193–249.
- Stecher, J., Shields, T., & Dickhaut, J. (2011). Generating ambiguity in the laboratory. *Management Science*, 57(4), 705–712.

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.