Volatile Financial Networks:

How Small Changes in the Network of Interbank Lending Lead to Big Changes in Financial Stability*

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Abstract

Since 2008, economists have used the network of bank-to-bank lending to understand and prevent another financial crisis. In this paper, I analyze the effect a single loan in this network can have on increasing or decreasing financial stability. I find that the addition or removal of a single loan can lead to an increase of an order of magnitude in unpaid loans and bank collapses. Because networks are inherently discontinuous objects, missing a single link in this network can mean predicting economic stability when disaster is imminent and vice versa.

Keywords: Financial Networks, Volatility, Financial Stability

JEL Classifications: D85, E44, G21, L14.

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1. Introduction

Since the 2008 financial crisis, macroeconomists and policy makers have been working to prevent such a combination of disasters from ever occurring again. Regulations have been implemented. [17] [13] Bailouts have been criticized and defended. [6] Network terminology like "cascading failures" has been added to the economic lexicon. [4] [7] [9] [11]

With the collapse of Lehman Brothers in September of 2008, an inability to repay debts spread like a contagion throughout the financial sector. Banks across the country struggled and many followed Lehman Brothers in declaring bankruptcy. These cascading bank failures were one of the reasons that the Great Recession was so devastating. [13] The US saw double digit unemployment, home values fell by 40%, and savings and retirement account balances dropped by almost a third. [17] Preventing such a downturn from happening again is an important task for economic researchers.

One of the most important tools in the post-2008 researcher's toolbox is the application of network theory to the network of bank-to-bank loans. Networks have been used to improve engineering, computer science, medicine, even air travel. [15] [3] But after 2008, they became key to understanding how negative shocks propagate from bank to bank throughout the economy.

Lots of work has been done in understanding how the overall structure of the interbank lending network affects financial stability. [10] [16] [9] Many researchers have characterized the simultaneously robust and also fragile nature of networks in the face of negative shocks. [2] [4] If the interbank lending network is too interconnected, it serves to propagate the shock to many banks throughout the network. If it is not interconnected enough, banks must rely on only a few banks for repayment and are particularly vulnerable to the shocks. Acemoglu, Ozdaglar, and Tahbaz-Salehi (2015), for example, analyze this robust/fragile dichotomy and characterize the level of connectivity at which a financial network tips from robust to fragile. [2]

However, little work has been done in understanding how changes at the individual loan level affect financial stability. Networks are discrete and discontinuous objects. Their ability to model individual connections between hundreds, even thousands, of agents is incredibly useful but also finicky. One little change in who is lending to whom can lead to large changes in the financial outcomes when a negative shock occurs. That is the purpose of this paper: to show what a difference a single link in the network - a single loan - can make.

To analyze the effect a single link can have, I use the network model of interbank lending described in Acemoglu et al. (2015). [2] In this model, banks lend to one another. These loans between the banks create links and all of these links and banks taken together constitute a *financial network*. The banks invest in projects outside of the network and these projects have random returns. These investments along with loan liabilities and assets determine the amount of their loans that banks can repay in equilibrium. When the random returns are particularly low, this creates a negative financial shock and these shocks can travel throughout the network via the loan relationships. This is how cascading financial failures occur.

In the following section, I describe the model and explore an example that demonstrates how the particular links of the network affect loan repayments. This example shows the mechanisms by which large financial changes can result from small changes in who borrows from whom. In this example, the addition of a single borrower increases a bank's equilibrium repayment amount to his lender. This in turn increases the lender's repayment, and their lenders' lenders' repayments, and so on.

Next, I simulate this model. I generate many random networks of loans, create a negative financial shock, change one link in the network - either by adding, removing, or switching a link - and then create the same negative financial shock. I compare the financial outcomes before and after this change. Specifically, I measure the number of loans that are not repaid in full, the total dollars that go unpaid, and the number of banks in the network that are unable to pay their loans in full, and I compare these measures before and after I modify the network by one link. I fix all of the loan amounts and interest rates to be the same for every loan so that any changes in the financial outcomes must be driven by changes in the links of the network rather than by differences in the individual banks' loans.

These simulations show that a small change - the addition, removal, or alteration of a single link - in the network can lead to enormous decreases in financial stability. In the presence of the same negative economic shock, two financial networks that differ by only one loan can see hundreds of millions of dollars more in unpaid loans. The number of banks that fail to pay their loans in full can increase by an order of magnitude. The change in financial outcomes that result from a single loan vary widely because of the links in the network of lending. Adding, removing, or switching a link can lead to hundreds more unpaid loans, hundreds of millions more unpaid dollars, and dozens more bank failures. All three of these small changes in network structure lead to similar (high) levels of variability in outcomes.

There are currently $5,315$ Federal Deposit Insurance Corporation (FDIC) insured institutions in the United States. This means that the US interbank lending network consists of $5,315$ nodes.

[8] There is currently no data set that describes all of the lending relationships that exist between these banks. A few researchers have come up with creative ways to estimate [12] [18] or calibrate and simulate [5] [14] the network that describes these relationships. But as I show in this paper, networks are so discontinuous that even if researchers are able to estimate a network with 99% of the correct links, that 1% can lead to predicting a stable economy when, in fact, financial crisis is right around the corner.

Many resources and a great deal of energy have been devoted to preventing another financial crisis like the one that began in 2008. One of the most important areas of this research is devoted to analyzing the network of interbank lending through which negative shocks propagate. The structure of this network - who borrows from whom - plays a large role in financial stability. A change in a single link - a single loan - can mean hundreds more unpaid loans, hundreds of millions more unpaid dollars, and a tenfold increase in banks that are unable to repay their loans. As such, going forward, we should devote some of these crisis-prevention resources to collecting detailed data that describes the *entire* network of interbank loans.

2. The Network of Loans

2.1. Model

In this model, there are n banks. These banks invest in projects and lend money to one another. This interbank lending is the focus of this paper. The loan relationships are links between banks and these links form a network. I use the convention that if bank j borrows from bank i, there is a link *from* bank j to bank i, indicating the flow of loan *repayment*. For example, in Figure 1, bank 1 owes a repayment to bank 2, bank 2 owes a repayment to bank 3, and so on. The ability of any single bank to repay their loans depends on their debtors repaying them. Their debtors repayment depends on their debtors' debtors and so on. In this way, the successful repayment of any loan depends on the network as a whole.

I use the model of lending and repayment described in Acemoglu, Ozdaglar, and Tahbaz-Salehi (2013). [2] Each bank j is endowed with k_j dollars that it allocates to investment, lending, or holding as cash and the bank borrows from one or more other banks. Let l_{ij} be the amount borrowed by bank j from bank i. With an associated interest rate of ρ_{ij}, the amount that bank j owes to bank i in repayment - the face-value of the loan - is $y_{ij} = (1 + \rho_{ij})l_{ij}$. Let r_{ij} be the equilibrium repayment amount that bank j pays to bank i: $r_{ij} \in [0, y_{ij}]$. If bank j does not borrow from bank i, then $y_{ij} = r_{ij} = 0$. In this paper, I set all of the non-zero loan amounts and interest rates, and thus face-values, to be the same. This is to ensure that differences in outcomes are driven by the structure of the networks - which links exist and who is connected with whom - rather than by differences in loan amounts.

In addition to lending and borrowing, the banks invest in projects. These projects can be small businesses, home loans, etc. Each bank invests in one project, although that project can be interpreted as an aggregation of several projects. These projects have a random component to their return; they can go very well or very poorly. The banks observe a preliminary random return, z_j, and upon observing this they can decide to liquidate some or all of the project. If they choose not to liquidate, they receive a fixed non-pledgeable yield, A. If they do liquidate, they can recover a fraction, ξ, of the project. This random return is the mechanism by which economic shocks occur. If this return is particularly low, it constitutes a negative shock and if it is particularly high it constitutes a positive economic shock.

Banks also have a senior obligation, v, that they must pay before they pay their junior obligations, the repayments of loans to other banks. This senior obligation encompasses operating costs as well as any senior creditors. First, loans and investments are made. Then random returns come in, liquidation decisions are made, and repayments of both senior and junior rank are disbursed. Finally, investment projects that were not liquidated yield their return, A.

Each bank's cash flow, h_j, consists of however much of their endowment they held in cash, c_j, the random return on their investment, z_j, and any loan repayments that they receive, $h_j = c_j + z_j + \sum_{k \neq j} r_{jk}$. If this cash flow is sufficient to cover all of the bank's obligations, the bank pays all of its loans in full. If it is not, the bank liquidates its project. The equilibrium repayments, r_{ij}, of each bank depend on that bank's equilibrium liquidation amount, L_j. Both repayments and liquidations depend on the repayment amounts of other banks. The equilibrium repayments and liquidation of bank j are given by:

$$r_{ij} = \frac{y_{ij}}{y_j} \max[\min\{y_j, h_j + \xi L_j - v\}, 0]$$

$$L_j = \max[\min\{\frac{1}{\xi}(v + y_j - h_j), A\}, 0]$$

The repayments made by any given bank depends on the repayments made by other banks throughout the network; the repayments made by other banks appear in the right-hand side of both equations.

In Figure 1 (c), bank 3 has only one repayment owed from another bank: bank 2. So $h_3 = c_3 + z_3 + r_{32}$. Bank 3 owes three different repayments, one each to banks 4, 9, and 10. As such, $y_3 = y_{43} + y_{93} + y_{103}$. The repayments and liquidation amount for bank 3 are then:

$$r_{43} = \frac{y_{43}}{y_3} \max[\min\{y_3, c_3 + z_3 + r_{32} + \xi L_3 - v\}, 0]$$

$$r_{93} = \frac{y_{93}}{y_3} \max[\min\{y_3, c_3 + z_3 + r_{32} + \xi L_3 - v\}, 0]$$

$$r_{103} = \frac{y_{103}}{y_3} \max[\min\{y_3, c_3 + z_3 + r_{32} + \xi L_3 - v\}, 0]$$

$$L_3 = \max[\min\{\frac{1}{\xi}(v + y_3 - (c_3 + z_3 + r_{32})), A\}, 0]$$

In these equations, r_{23}, the repayment from bank 2 to bank 3, directly affects the repayments to banks 4, 9, and 10, and thus indirectly affects any banks that receive repayments from those banks or those banks' lenders, and so on.

2.2. Example

In the network of interbank loans, every loan repayment from one bank to another depends upon all of the other repayments - either directly or indirectly - taking place throughout the network. Consider the following example that demonstrates what a large effect a single link can have.

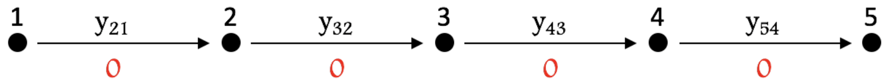
Suppose that five of the n banks in the network are connected in the way shown in Figure 1 (a). Bank 1 borrowed from bank 2 and now owes bank 2 the face value, y_{21}. Bank 2 owes bank 3 y_{32}, bank 3 owes bank 4 y_{43}, and bank 4 owes bank 5 y_{54}. Banks 2, 3, 4 and 5 only have the one borrower. That is, they only have the one repayment coming in.

Suppose that, based on the cash that bank 1 has coming in, h_1, bank 1 is unable to repay any amount to bank 2, $r_{21} = 0$. Further suppose that, because bank 2's only repayment, r_{21} is 0, bank 2 does not have enough funds to cover its senior obligation, v. That is $h_2 + \xi A - v =$

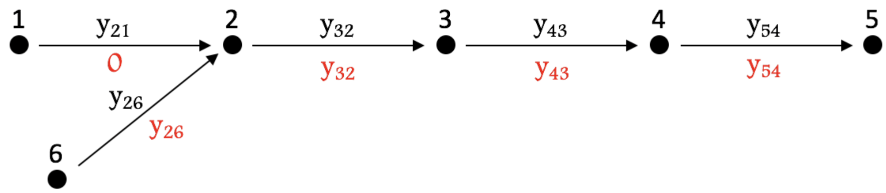
$(c_2 + z_2 + 0) + \xi A - v < 0$ and therefore bank 2 cannot repay its loan either, so $r_{32} = 0$. This can in turn lead to $r_{43} = 0$ and $r_{54} = 0$, because the other banks only have the one repayment coming in and these repayments are all 0. This means that their cash flow, h_j, even in combination with a fully liquidated project, ξA, is not enough to cover their senior obligation, v, and therefore their junior creditors - the other banks - get nothing.

Now suppose instead that there is a link from another bank, bank 6, to bank 2, as shown in Figure 1 (b). That is, bank 2 now has a second repayment coming in. Suppose bank 6 is able to repay the loan in full, $r_{26} = y_{26}$. If this repayment is large enough to not only cover bank 2's senior obligation, v, but also the repayment that it owes to bank 3 - $h_2 + \xi l_2 - v > y_{32}$, which is perfectly mathematically and economically feasible if the repayment from bank 6 is large enough - then bank 2 can repay its loan in full. As a result, $r_{32} = y_{32}$ and bank 3 receives its full repayment, and it too can repay its loan in full, $r_{43} = y_{43}$, and bank 4 does too, $r_{54} = y_{54}$.

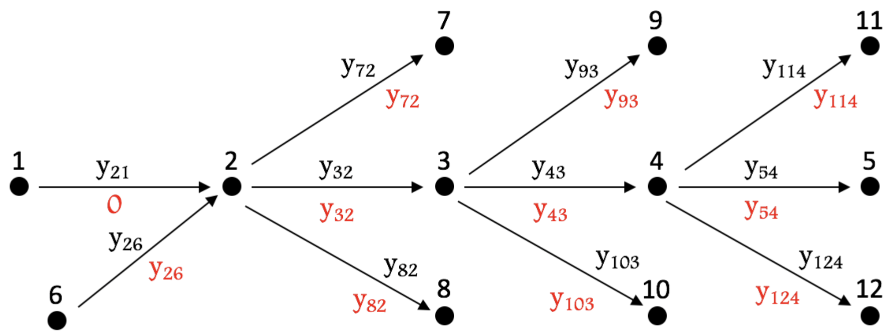
Before there is a link from bank 6 to bank 2, of the $y_{21} + y_{32} + y_{43} + y_{54}$ total dollars owed by these banks, 0 dollars are repaid. When the link does exist, $y_{32} + y_{43} + y_{54}$ dollars are repaid. This is the difference between no successful repayments and most of the loans being successfully repaid, simply because one link changed. If banks 2, 3, or 4 owed multiple repayments to other banks in the network, as depicted in Figure 1 (c), the change would have been even more dramatic. In a network of many banks, this type of change can occur many times over. This is how a small change in one link can lead to large changes in outcomes across the entire network.



(a)



(b)



(c)

Figure 1: Network Structure's Effect on Loan Repayment

3. Simulation Results

To demonstrate the effect that a single link in the network of loans has on aggregate loan repayment outcomes, I simulate the model described in the previous section. In each simulation repetition, I first generate a random network of loans. Then, I find the repayment equilibrium in the presence of a negative financial shock. Then, I change a randomly selected link in one of three ways: (1) add an link where there was not one previously, (2) remove a link from the network, or (3) move a link from one place in the network to another. Finally, given this new network, I find the new repayment equilibrium in the presence of the same negative shock. I compare aggregate financial outcomes between the original and modified networks.

The randomly generated networks in this simulation consist of 100 banks. Real world financial networks consist of between 27 banks (Mexico) and $5,315$ banks (the United States). [5] [8] Every additional bank included in the network approximately doubles the computation time required to compute a single equilibrium and 100 banks is sufficient to demonstrate the significance of changing a single link in the network.

If banks cannot lend to themselves, that is, there are no *self loops* in the network, then there are $100 \times 99 = 9,900$ possible links that could exist between the banks. I perform $9,900$ Bernoulli trials, each with a probability of success of 0.5. If the result of the Bernoulli trial is a 1, the associated link is present in this particular network. If the result is a 0, that link is not present in this network. I place the resulting 1 or 0 in the appropriate location in the adjacency matrix and this describes the randomly generated network. The diagonal values are set to 0 because banks cannot lend to themselves. This adjacency matrix, M, describes which banks lend to which; if $m_{ij} = 1$, there is a loan from bank i to bank j and bank j owes bank i repayment. The value of each loan is set to \$100 million and the interest rate for each loan is set to 2.7%, the average London Inter-Bank Offered Rate in the months preceding this simulation. [1] See the online Appendix for a full description of the model parameterization used in this simulation.

To randomly add a link to a given network, I locate all available locations (0's in the adjacency matrix, M) and randomly and uniformly select one. This selected 0 is changed to a 1. To randomly remove an existing link, I identify all of the links present in the network (1's in the adjacency matrix, M) and randomly and uniformly select one to remove. This 1 is switched to a 0. Finally, to switch a link, I randomly remove an existing link and then randomly add one. In this case, the number of links in the network remains unchanged but the location of a single link - the identity of the borrower and the identity of the lender - changes.

I compute the repayment equilibrium described in the previous section before and after the network is modified by adding, removing, or switching a link. I use three different measures of the financial instability generated by the negative financial shock: the number of loans that fail to be paid in full, the total unpaid dollar value of those loans, and the number of banks that are unable to pay their loans in full. I then take the difference in these three measures before and after the network is modified.

I run 200 repetitions of each network modification. That is, I run 200 repetitions in which I add a link, 200 repetitions in which I remove a link, and 200 repetitions in which I switch a link, for a total of 600 repetitions. In each of these 600 repetitions, I find an original repayment equilibrium and a new repayment equilibrium after the modification, for a total of $1,200$ equilibrium computations.

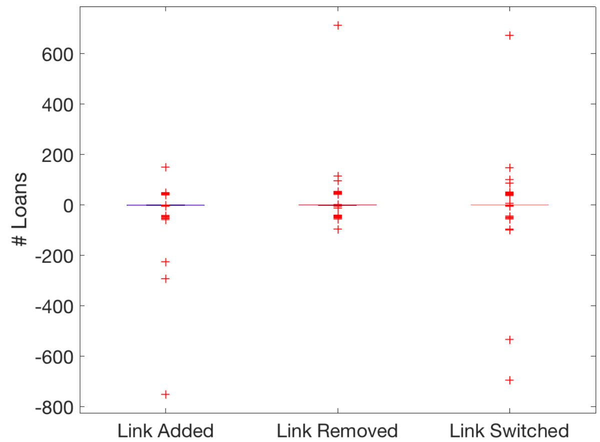
Table 1 and Figure 2 describe the changes to financial stability that result from these three different modifications.

Table 1: Changes in Financial Stability

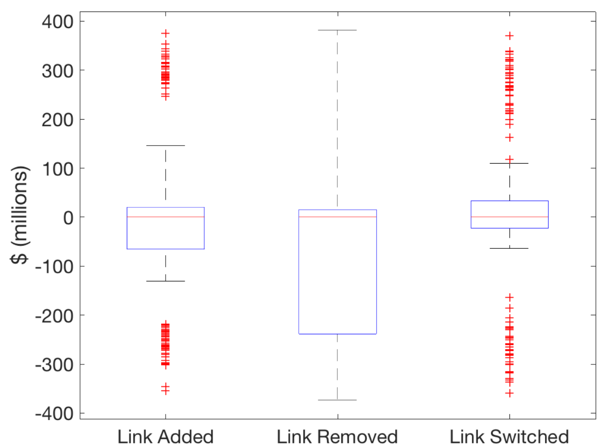
Change (original - mod) in:	Mean	Std. Dev.	Min.	Max.	p-value
Link Added					
# Loans	-7.335	63.193	-751	151	0.1025
Loan $'s (mill.)	-1.663	188.195	-354.51	375.55	0.9756
Banks	-0.15	2.977	-25	18	0.4768
Link Removed					
# Loans	6.17	55.426	-96	715	0.1167
Loan $'s (mill.)	-43.651	188.203	-373.83	382.14	0.0017
Banks	0.205	2.262	-5	26	0.1905
Link Switched					
# Loans	19.97	330.264	-693	$4,524$	0.6465
Loan $'s (mill.)	4.506	191.119	-848.03	370.81	0.4958
Banks	0.195	3.769	-24	27	0.7945

Each measure considered is a series describing the difference between a financial outcome before and after the network of loans is modified. Only one difference's mean was statistically significantly different from 0: the total dollars that go unpaid after a link is removed. The p-values from a paired t-test are reported in Table 1. The null hypothesis is that the samples have a mean of 0, indicating that the means of measures are the same before and after the modification of the network. This null hypothesis cannot be rejected at the 5% level in all but one case: unpaid loan dollars when a link is removed.

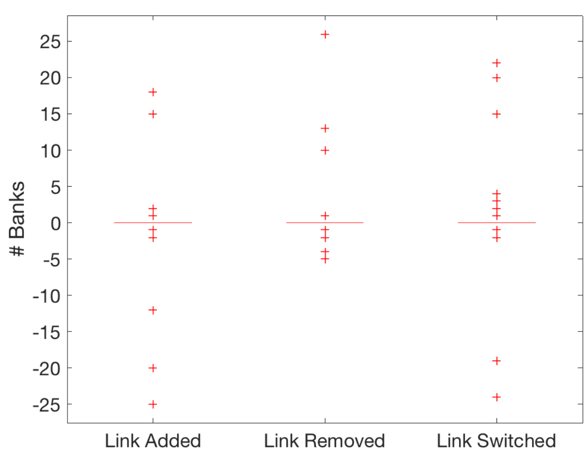
The focus of this paper is not, however, on the average outcomes but on the spread and extreme outliers of these differences. Figure 2 shows box plots of each series. The boxes, which can only be distinguished in the middle panel, designate the data points that lay within the 25th and 75th percentiles. The whiskers of the plots extend to the 1st and 99th percentiles. The *outliers* are designated with a "+". All three of these modifications lead to differences with many outliers. These box plots and the standard deviations reported in Table 1 indicate that these samples have many observations in the extreme ends of the distribution; they have many very high values and many very low values.



(a) Change in Unpaid Loans



(b) Change in Unpaid Dollars



(c) Change in Delinquent Banks

Figure 2: Changes in Loan Outcomes

For all three modifications and all three measures of financial outcomes, changing the network can lead to much worse outcomes. Adding a link led to as many as 751 more unpaid loans, \$354.51 million more unpaid, and 25 more banks unable to pay their loans in full in the network with the additional link. Switching a link can lead to 693 more unpaid loans, \$848.03 million more unpaid, and 24 more banks unable to pay their loans in full. Removing a link leads to fewer extreme outcomes compared to the other two modifications; it can lead to 96 more unpaid loans, \$373.83 million more unpaid, and 5 more delinquent banks in the network with the link removed, in the most extreme cases.

The modifications can also lead to increased financial outcomes. In the extreme cases, switching a link can lead to an incredible $4,524$ fewer unpaid loans,[1] \$370.81 million fewer unpaid, and 27 fewer banks who cannot pay their loans in full. Adding a link can lead to 151 fewer unpaid loans, \$375.55 million fewer unpaid, and 18 fewer delinquent banks. Removing a link can lead to 715 fewer unpaid loans, \$382.14 million fewer unpaid, and 26 fewer delinquent banks.

Not only do such extremes exist, but they are not uncommon. The standard deviation of each these series describes how widely spread the data is. It describes how far the data points are from their mean, in general. The change in delinquent banks has a standard deviation between 2 and 4 banks, but the changes in unpaid loans and unpaid dollars are both widely spread. The change in unpaid loan dollars has a standard deviation of about \$190 million in all three modifications. When a link is added or removed, the number of unpaid loans has a standard deviation between 55 and 65 loans, but when a link is switched, the standard deviation is 330 loans.

These simulation data indicate that a small change in the network of interbank lending can lead to enormous changes in financial stability. It may be an increase in financial outcomes, as demonstrated by all of the data points in the top half of the box plots in Figure 2. But such a small change can lead to large decreases in financial outcomes, as well, as shown by all of the data points in the bottom half of the box plots. These points in the bottom half represent simulation repetitions in which the number of unpaid loans, unpaid loan dollars, or banks unable to repay their loans in full were much larger after the network of loans changed by just one single link.

[1] This outlier is omitted from the data used to create the box plots so that all three differences can be reasonably displayed on the same axis.

4. Conclusion

In this paper, I showed what a difference a single link in the network of interbank loans can make in financial stability. Whether a new loan is added, an existing loan is removed, or the identities of the lender and borrower are changed, the ability of the banks in the network to repay their loans can vary widely. These small changes in the network can lead to several hundred more unpaid loans, hundreds of millions more unpaid dollars, and dozens more bank failures. The harm or help provided by just one loan can be amplified dramatically by the links that exist between banks throughout the network. The next logical step in this research is to identify what types of financial network and what types of loans we should be on the lookout for, that is, the types that lead to increased or decreased financial stability.

The goal of this paper is to characterize the power of a single link in the network. It is also to emphasize the need for data that describes the entire *universe* of loans between banks. The omission of a single link from this data could mean we predict a rosy outcome when disaster is coming and vice versa.

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The data generated in the simulations are available from the author upon reasonable request.
Declarations of interest: none