Missing Financial Network Data

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Abstract

Little data exists describing the links of the US financial network. Using a computational model of interbank lending, I show that this lack of data can lead to erroneous model predictions. I analyze several types of data inaccuracies and find that missing a single loan in the network can lead to large differences in the predicted number of unpaid loans and total dollars repaid. This missing data could mean implementing policies that are designed to improve macroeconomic stability but that could actually lead to substantial destabilization. These results are robust across multiple network sampling regimes.

Keywords: Financial Networks, Financial Stability, Missing Data

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 financial disaster from ever occurring again. 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 (Lioudis 2023). The US saw double digit unemployment, home values fell by 40%, and savings and retirement account balances dropped by almost a third (Silver 2022). Preventing such a downturn from happening again is an important task for economic researchers and policy makers. With the 2023 collapse of Silicon Valley Bank and Signature Bank came renewed fears of financial contagion and a renewed focus on preventing cascading bank failures (Sherter 2023). Accomplishing this task requires a thorough understanding of the particular lending relationships that exist between banks. This paper demonstrates the effect that missing data can have on our ability to accomplish this task.

Theoretical work has been done in understanding how the the interbank lending network as a whole affects financial stability (Jackson 2010; Schweitzer et al. 2009; Hasman 2013). Researchers have characterized the simultaneously robust-yet-fragile nature of networks in the face of negative shocks (Acemoglu, Ozdaglar, and Tahbaz-Salehi 2015; Chinazzi and Fagiolo 2013). 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. However, little empirical work exists on this question because there is no data set that describes the specific loan relationships that exist in the US financial system.[1]

In contrast, this paper explores the effect a single link in the network can have on financial outcomes, such as loan repayment and bank default. To do this, I adapt the network model of interbank lending described in Acemoglu, Ozdaglar, and Tahbaz-Salehi 2015. While Acemoglu and co-authors use this model to explore the effect of the overall structure of the network on financial stability, I use the model to understand how small changes in the bank-to-bank loan relationships affect aggregate financial outcomes. Mine is a bottom-up analysis of the effect of micro-level changes on macroeconomic outcomes. I use this model because it is well-established in the financial network

1. This is not true for all countries. Imai and Takarabe (2011) use data describing banks in Japan to investigate whether banking integration contributes to the propogation of financial contagion (Imai and Takarabe 2011).

literature and will allow for a focus on the specific loans that do and do not exist. I measure three outcomes in the model: the number of interbank loans that are repaid in full, the loan dollars that are repaid, and the number of banks that are able to repay their loans in full.

In the 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. The results of these investments, along with the banks' other assets, determine the amount of their loans that banks are able to 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 an example that demonstrates how the particular links of the network affect loan repayments. This example shows the mechanisms by which large changes in loan repayment and bank stability 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 the lenders' lenders' repayments, and so on. This demonstrates how missing a single loan in the data can lead to dramatically under - or over - estimating the financial well-being of the banking sector.

Next, I simulate the model. I generate many random networks of loans, implement 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. Each of these network modifications demonstrates the effect of a specific type of data error: missing a link (loan) in the network that is actually present, incorrectly including a link that is not actually present, and including a link between the wrong two banks, respectively. 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. I compare the outcomes before and after these changes. 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. I compare these measures before and after I modify the network by one link.

These simulations show that a small error in the network data can lead to enormous changes in the model's predicted 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 difference in unpaid loans. This means that model predictions can be off my hundreds of millions of dollars. The average difference in the number of loan dollars that are repaid is between 5 and 22 million dollars, depending on how the two networks differ. Even more remarkable than the average differences is the variability in these differences. The standard deviation of the change in unpaid loan dollars is between 184 and 234 million dollars. 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 data errors in network structure lead to similar (high) levels of variability in outcomes.

These results are robust to multiple types of network structure and formation. I perform the above analysis for two types of random network sampling: (1) networks in which each possible loan relationship has the same probably of occurring and (2) scale free networks in with the degree distribution follows a power law. The variance in outcomes in the latter sampling method is smaller than in the former, but both demonstrate substantial differences in aggregate financial outcomes.

There are currently 4,703 Federal Deposit Insurance Corporation (FDIC) insured institutions in the United States (Federal Deposit Insurance Corporation 2023). This means that the US interbank lending network consists of 4,703 nodes. 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 (e.g Kuo et al. 2013 and Taschereau-Dumouchel 2017) or calibrate and simulate (e.g. Cuenda, Fernández, and Galeano 2018 and May, Levin, and Sugihara 2008) the network that describes these relationships. But as I show in this paper, network outcomes are so discontinuous that even if researchers are able to estimate a network with 99% of the correct links, that remaining 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. Missing a single link - a single loan - in the data can mean measuring 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.

Implementing good financial regulatory policy requires a thorough understanding of the interbank lending network. If policy makers do not account for the links that exist between banks or if they do not have data describing the correct links, policies designed to stabilize the financial sector could actually destabilize it.

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 2015. 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 depend 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.

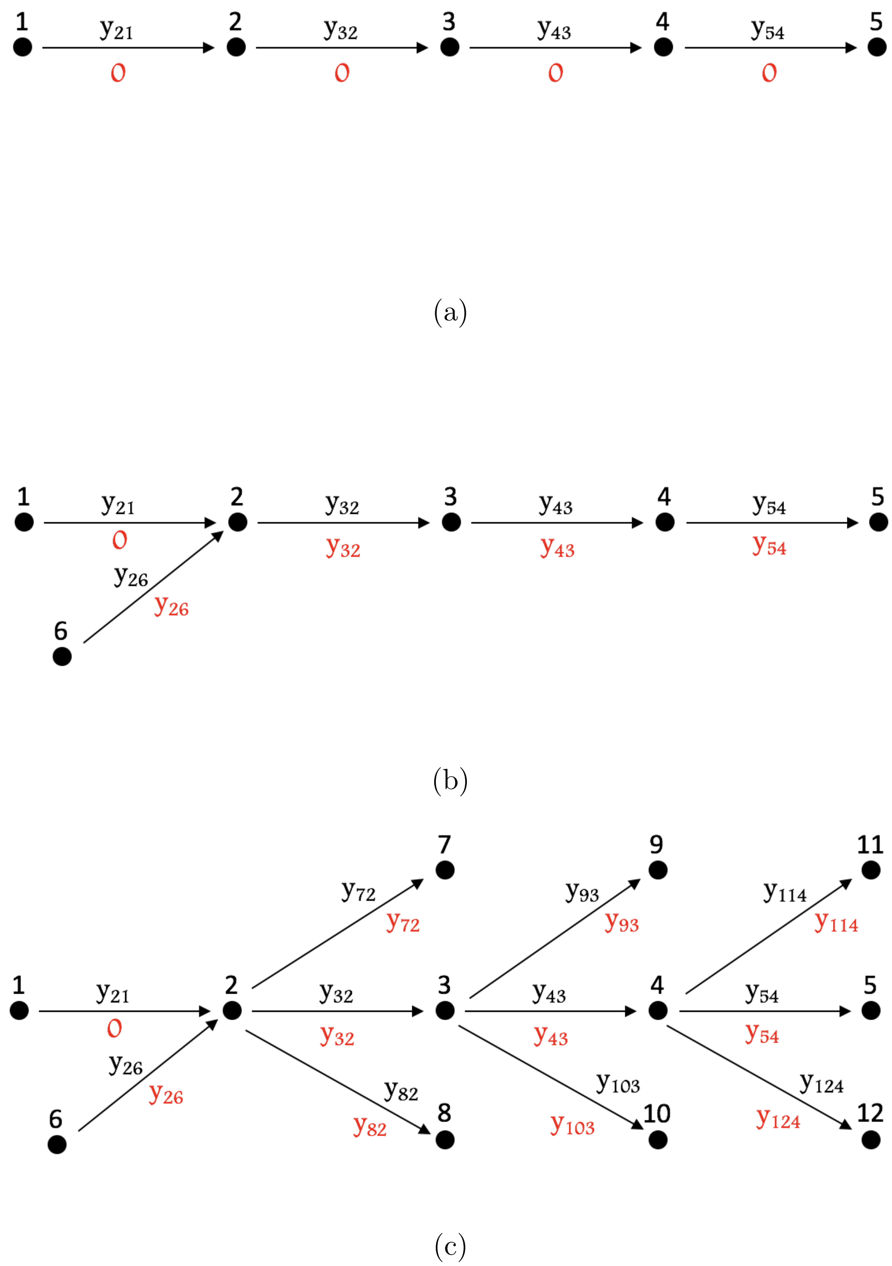


Figure 1: Network Structure's Effect on Loan Repayment

Note: This figure provides an example demonstrating the effect that one additional link can have on the entire network of banks' abilities to repay their loans. In panel (a), none of the banks are able to repay their loans. In panel (b), with the addition of the link from bank 6 to bank 2, almost all of the banks are able to repay their loans. In panel (c), the effect of the additional link is even larger because of the additional downstream banks.

3. Simulation Results

To demonstrate the effect of the error of a single link in the network of loans 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 a 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. If this resulting new network represents the true network and the network before the modification represents the data we have access to, these modifications correspond to three measurement errors: (1) missing a link that is actually present, (2) erroneously including a link that is not actually present, and (3) including a link between two banks that is actually between two different banks.

The randomly generated networks in this simulation consist of 100 banks. Real world financial networks consist of between 27 banks (Mexico) and 4,307 banks (the United States) (Cuenda, Fernández, and Galeano 2018; Federal Deposit Insurance Corporation 2023). 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 (Macrotrends 2019). See the online Appendix for a full description of the model parameterization used in this simulation. I discuss an alternative network sampling method in the next section.

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.

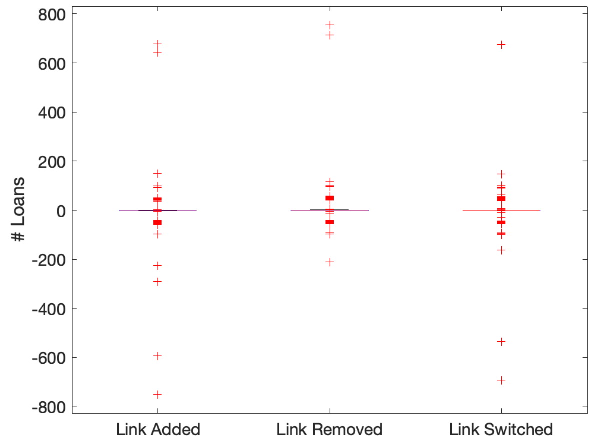
I run 400 repetitions of each network modification. That is, I run 400 repetitions in which I add a link, 400 repetitions in which I remove a link, and 400 repetitions in which I switch a link, for a total of $1,200$ repetitions. In each of these $1,200$ repetitions, I find an original repayment equilibrium and a new repayment equilibrium after the modification, for a total of $2,400$ equilibrium computations.

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

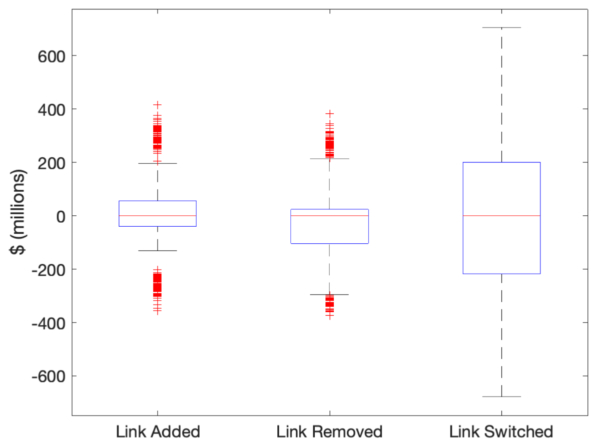
Table 1: Changes in Financial Stability					
Change (original - mod) in:	Mean	Std. Dev.	Min.	Max.	p-value
Link Added					
# Loans	−2.15	73.87	−751	678	0.5617
Loan $'s (mill.)	−10.67	192.44	−354.51	416.48	0.2680
Banks	0.01	3.00	−25	22	0.9335
Link Removed					
# Loans	5.45	58.30	−211	756	0.0624
Loan $'s (mill.)	−22.58	184.49	−373.83	382.14	0.0149
Banks	0.17	2.29	−16	26	0.1317
Link Switched					
# Loans	−1.95	62.64	−693	675	0.5350
Loan $'s (mill.)	−5.36	234.45	−678.71	706.40	0.6483
Banks	−0.04	2.63	−24	22	0.7612

Each measure considered is a series describing the difference between a financial outcome before and after the network of loans is modified. This describes the difference in the financial outcomes between the network described by the data (before) and the actual network (after). If the average is negative, it means that, on average, the financial outcome for the true network was larger than the financial outcome measured for the network described by the data. Similarly, if the average is positive, it means that, on average, the financial outcome measured for the true network was smaller than the financial outcome measured for the network described by the data. 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 the last column of 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. That is, if the true network does not contain a link but we erroneously include this link in the data, this error can lead to measuring a statistically significantly different number of loan dollars repaid.

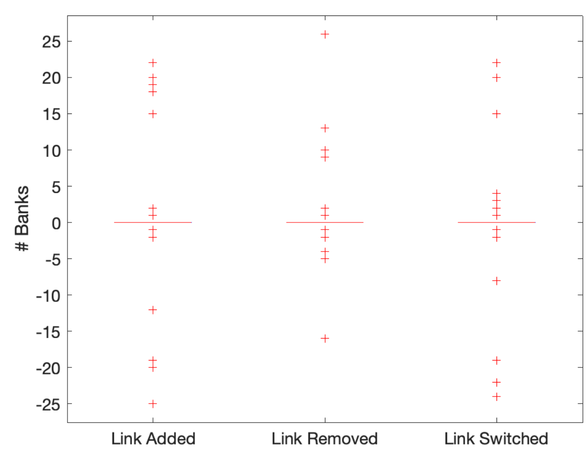
The focus of this paper is not, however, on the average outcomes but on the spread and extreme outliers of these differences. Figure 2 shows box plots of each series. The boxes, which can only be distinguished in the middle panel, designate the data points that lay within the 25th and 75th percentiles of their respective data sets. The whiskers of the plots extend to the 1st and 99th percentiles. The outliers are designated with a "+" in the Figure. 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

Note: This figure shows box plots of the differences in aggregate financial outcomes before and after a network modification of one link. These plots demonstrate that a substantial number of observations in the data lay outside the interquartile range. All of the data sets feature a large spread and extreme outcomes.

For all three types of measurement error and all three measures of financial outcomes, mismeasuring the network can lead to measuring much worse outcomes. Missing a link that is actually present led to measuring 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. Incorrectly including a link that is not actually present can lead to measuring 211 more unpaid loans, \$373.83 million more unpaid, and 16 more banks unable to pay their loans in full. Attributing a link to the wrong banks can lead to measuring 693 more unpaid loans, \$678.71 million more unpaid, and 24 more delinquent banks in the network.

These types of measurement error can also lead to measuring better financial outcomes. Missing a link that is actually present can lead to measuring 678 fewer unpaid loans, \$416.48 million fewer unpaid, and 18 fewer delinquent banks. Incorrectly including a link that is not actually present can lead to measuring 756 fewer unpaid loans, \$382.14 million fewer unpaid, and 26 fewer delinquent banks. Attributing a link to the wrong banks can lead to measuring 675 fewer unpaid loans, \$706.40 million fewer unpaid, and 22 fewer banks who cannot pay their loans in full.

Recall that each loan in the network is for \$100 million. The changes in the measured amounts of repaid loan dollars represent between three and seven entire loans. There are, on average, $5,000$ links in each network, so these extreme changes in the number of repaid loans represent about 15% of the loans in the network. Finally, as there are 100 banks in each network, these extreme changes in measured delinquent banks represent about 20% of the banks in the network.

Not only do such extreme results exist, but they are not uncommon. The standard deviation of each of these series describes how widely spread the data is. The change in unpaid loan dollars has a standard deviation of about \$190 million in both when a link is incorrectly included and when a link is incorrectly not included. This is almost twice the size of the loan amount between banks in this experiment. When a link is added or removed, the number of unpaid loans has a standard deviation between 55 and 75 loans, which is large relative to the means, which are in the single digits.

These simulation data indicate that a small error - only one link - in the network of interbank lending can lead to enormous changes in the measured financial outcomes. 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.

3.1. Scale Free Networks

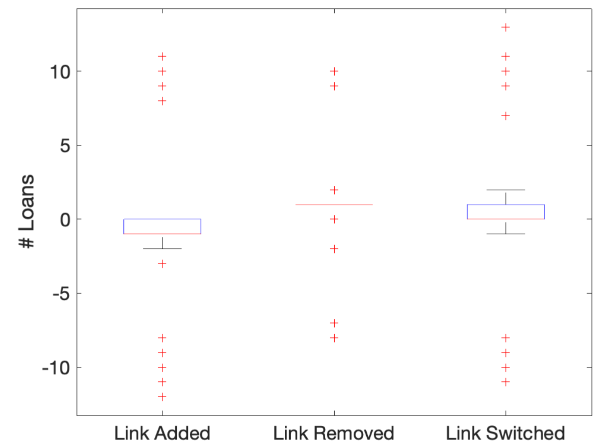
Many real-world networks, including many economic networks, are scale free. That is, the degree distributions of the nodes in the network follow a power law (Barabási 2009). There is evidence that social networks are scale free and some evidence that production networks are, as well (Konno 2009). However, due to the lack of data describing financial networks, it remains an open question whether such networks are scale free.

Because scale-free networks are so ubiquitous, I perform the same analysis as in the previous section on randomly generated scale-free financial networks. All other parameterizations of the model remain the same, the only change is how each initial network is randomly generated. I use the Barabàasi - Albert algorithm to randomly generate scale free networks, with an initial connected component consisting of 50 banks (Tapan 2015).

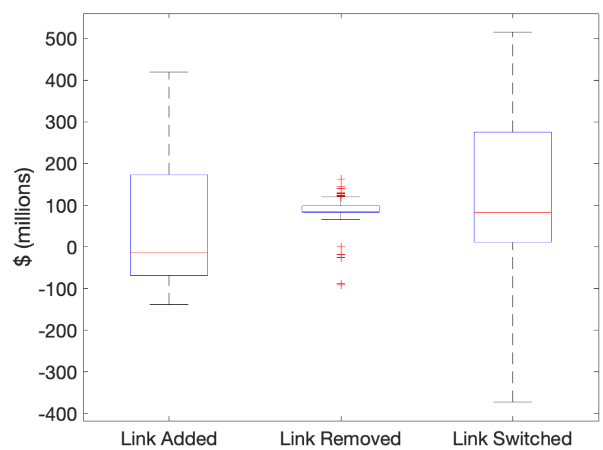
Sampling networks in this manner can generate networks for which the model is not defined. If there is a bank in the network that does not have a lending partner, the model is not defined and cannot be solved. As a result, it takes more repetitions to complete this experiment and there is a certain amount of stochasticity in how many repetitions of each measurement error are created. These simulations produced 505 network experiments in which a link was added, 469 in which a link was removed, and 501 in which a link was switched.

The table and boxplots from the previous section are replicated below with the scale-free data.

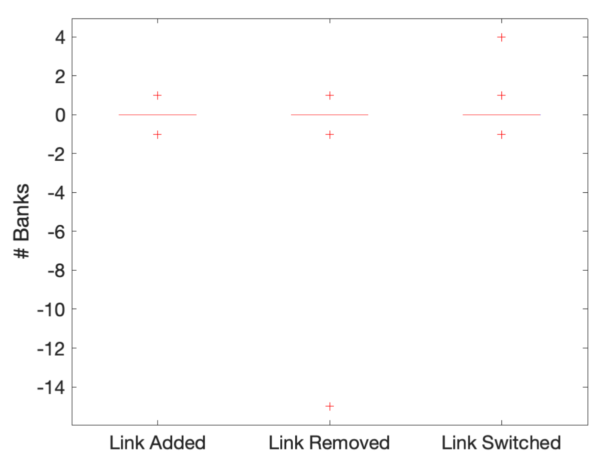
Table 2: Changes in Financial Stability (Scale Free)					
Change (original - mod) in:	Mean	Std. Dev.	Min.	Max.	p-value
Link Added					
# Loans	-0.780	2.11	-12	11	0.0000
Loan $'s (mill.)	60.38	176.81	-138.54	420.26	0.0000
Banks	-0.006	0.21	-1	1	0.5321
Link Removed					
# Loans	1.00	0.91	-8	10	0.0000
Loan $'s (mill.)	90.77	20.66	-91.44	162.86	0.0000
Banks	-0.03	0.70	-15	1	0.3565
Link Switched					
# Loans	0.29	2.27	-11	13	0.0045
Loan $'s (mill.)	152.42	180.57	-372.96	516.00	0.0000
Banks	-0.002	0.29	-1	4	0.8761



(a) Change in Unpaid Loans



(b) Change in Unpaid Dollars



(c) Change in Delinquent Banks

Figure 3: Changes in Loan Outcomes (Scale Free)

Note: This figure shows box plots of the differences in aggregate financial outcomes before and after a network modification of one link when the random networks generated are scale free. While there are fewer outliers in these series, these data sets also feature a large spread and extreme outcomes.

The boxplots and the standard deviations reported in Table 2 indicate that the changes in measured financial outcomes are less widespread than in the uniformly sampled network case. There are fewer extreme outliers and the standard deviations are smaller, except in the case of repaid loan dollars.

Notably, for every type of measurement error, there is a statistically significant difference in the measured number of repaid loans and repaid loan dollars. As in the previous section, p-values from a paired t-test are reported in the last column of Table 2. 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 is rejected in every case except the number of delinquent banks. This indicates that, in terms of number of loans repaid and the total dollars repaid, these measurement errors create a statistically significant difference in the measured financial outcomes.

4. Conclusion

In this paper, I showed what a difference a mistake in a single link in the network of interbank loans can make in measured 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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5. Appendix

5.1. Model Parameterization in Simulations

Table 3: Model Parameterization

Parameter	Value
Number of Banks, n	100
Loans size, l_{ij}, in millions of dollars	100
Interest rate, $\rho_{ij} = \rho$	0.027
Negative shock, z_j	0.01
Mature project yeild, A_j, in millions of dollars	7
Fraction recoverable, ξ_j	0.4
Cash held, c_j, in millions of dollars	3
Senior creditor obligation, v_j, in millions	10