The Effect of Missing Financial Network Data on Predicted Financial Outcomes

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Abstract

Little data exists describing the links of the US financial network. Using a computational model of interbank lending, we show that this lack of data can lead to erroneous model predictions. We find that missing a single loan in the network can lead to large differences in the predicted aggregate repayments across the entirety of the network of banks. This missing data could mean implementing policies that are designed to improve macroeconomic stability, but that could actually lead to substantial destabilization.

Keywords: interbank lending; financial networks; incomplete data

JEL Classifications: C63, E58, G21, L14

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1. Introduction

Since the 2008 financial crisis, macroeconomists and policymakers 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 2019). The US saw double-digit unemployment, home values fell by 40%, and savings and retirement account balances dropped by almost a third (Silver 2019). These effects were especially felt by groups historically excluded from the banking system (Blanco, Contreras, and Ghosh 2022). Preventing such a downturn from happening again is an important task for economic researchers and policymakers. 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 prevent financial contagion.

Theoretical work has been done to understand 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]

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, we 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, we use the model to understand how small changes in the bank-to-bank loan relationships affect

[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 propagation of financial contagion (Imai and Takarabe 2011).

aggregate financial outcomes. Ours is a bottom-up analysis of the effect of micro-level changes on macroeconomic outcomes. We use this model because it is well-established in the financial network literature and will allow for a focus on the specific loans that do and do not exist.

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, we 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 its lender. This, in turn, increases the lender's repayment, 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, we calibrate and simulate the model. We generate many random networks of loans, implement a negative financial shock, and measure the amount of repayments each bank is able to make across the network. We then add a link/loan between two randomly chosen banks, implement the same negative financial shock, and remeasure the repayments. We compare the banks' ability to repay their loans across these two networks that differ by only one link and find substantial differences in the ability of banks across the whole network to repay their loans. These differences expand far beyond the new loan. The randomly generated lending networks are calibrated to match the observed degree distribution of the US lending network described in Soramäki et al. 2007. We 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 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 by 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 varies 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. Small errors in the network data fed into a model can lead to large changes in model outcomes.

There is currently no data set that describes all of the lending relationships that exist between the banks in the US lending network. 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 et al. 2018 and May, Levin, and Sugihara 2008) the network that describes these relationships. But as we 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. Policy-makers will be made better of by devoting 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 between banks or do not have data describing the correct links, policies designed to stabilize the financial sector could actually destabilize it.

2. Network Model

The focus of this paper is to model the dynamics of loan repayments within the US interbank lending network and the implications for economic stability. In this model, banks borrow and lend money to one another. These loans create a network of loans between banks. We use a model that incorporates cash flows, senior obligations, and equilibrium repayments. Interruptions to repayments can set off a chain reaction among interconnected banks. Through the introduction of missing data scenarios, such as adding or omitting loan links, this paper demonstrates how seemingly minor data errors can have significant repercussions on repayment cascades. Such cascades can lead to a surge in unpaid loans and even bank defaults.

We model the behavior of individual banks in the network. Each bank is obligated to repay its debts to other banks to the extent it can. We adopt a model from Acemoglu, Ozdaglar, and Tahbaz-Salehi 2015. We denote the face value of a loan from bank i to bank j as y_{ij}. Bank j repays to bank i some number r_{ij} between 0 and y_{ij}. The value of r_{ij} depends on the funds that bank j has at its disposal. Bank j's available resources depend not only on its additional cash and the investments it makes but also on the ability of its debtors to repay their loans. If there is no loan between two banks in the network, $y_{ij} = r_{ij} = 0$. The model therefore describes an equilibrium repayment network for all of the banks in the system. Our outcome of interest is the total dollars repaid across the network as a whole: $\sum_{i,j} r_{ij}$.

The amount banks repay to each other depends upon their current assets and obligations. Current obligations may prevent them from repaying interbank loans in full. These obligations consist of payments owed to firms, individuals, and other private and public entities. We denote these "senior obligations" that banks must repay before their loans as v_j. Included in this are taxes, wages, and rent. All senior obligations must be repaid in full before the payment of interbank lending can begin. Each bank j has an amount of cash on hand c_j, and accumulates a random return on its individual investment, A_j.

The repayment equilibrium is described by the system of repayment equations for each loan between bank i and bank j:

$$r_{ij} = \frac{y_{ij}}{y_j} \max\{\min\{y_j, c_j + A_j + \sum_{j \neq s} r_{js} - v\}, 0\} \tag{1}$$

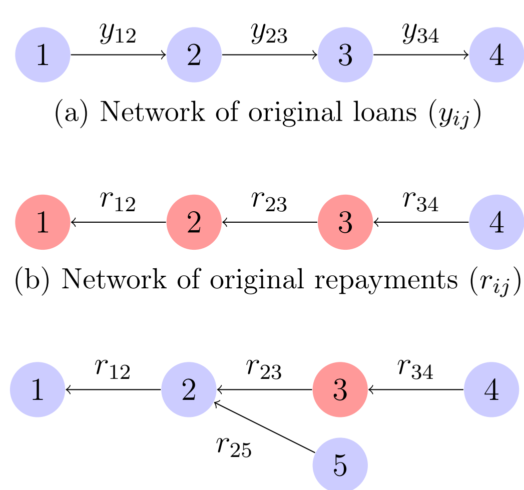
Let a bank's current assets be $h_j = c_j + A_j + \sum_{j \neq s} r_{js}$. A bank's ability to pay back interbank loans in full is determined by whether or not h_j is sufficient to cover both senior and interbank obligations. If h_j is insufficient to cover the repayment of senior obligations, bank j will be unable to repay its loan in full. Each bank's ability to repay other banks in the network is determined by the repayment quantities and consistencies of other banks. If $h_j - v > y_j$, then the bank can repay all of its total loan debt, y_j, in full and therefore repay each loan amount, y_{ij}, in full. If

$0 < h_j - v < y_j$, then bank j will repay each bank a fraction of the loan amount due, $\left(\frac{y_{ij}}{y_j}\right)(h_j - v)$. Finally, if $h_j - v < 0$, the bank defaults on all of its loans since it does not have enough cash on hand to cover its senior obligations.

2.1. Example

Here, we describe a small example that demonstrates how easily one small change in network structure can lead to large changes in total repayments. Since each bank relies on the payments of other banks within the network, the repayment model allows us to quantify the consequences of loan delinquency for the network as a whole. Suppose Bank 1 loaned to Bank 2 and Bank 2 to Bank 3 and so on, as shown in Figure 1. These loans denoted as y_{12} and y_{23} respectively. The amount that Bank 2 repays Bank 1, r_{12}, depends upon the repayments of Bank 3 to Bank 2 and Bank 4 to Bank 3, r_{23} and r_{34}. Suppose Bank 3 is delinquent on its loan due to a low return on its outside investments A_3, meaning the loan from the Bank 2 is not paid back in full. As a result, Bank 2 does not have enough assets to cover enough senior obligations or to repay their loan in full from Bank 1, making Bank 2 delinquent on their loan, as seen in Figure 2.

Figure 1: Repayment Example



(c) Network of new repayments with an added link(r_{ij})

Notes: The index order remains the same between y_{ij} and r_{ij} while the directionally of the links reverse

However, consider if, when measuring this network in data, the researcher missed a link in the network of loans from Bank 2 to Bank 5, y_{25}. If Bank 5 had a good return on their outside investments and can repay their loan in full, this will allow Bank 2 to repay its loan to Bank 1 in full, preventing the cascading bank failures that could lead to a financial system crash. The researcher may have incorrectly predicted financial collapse. The outcome could go the other way, as well: researchers may predict financial stability when cascading financial failures are imminent simply by missing a link in the network. This example is magnified when we incorporate more banks into the network.

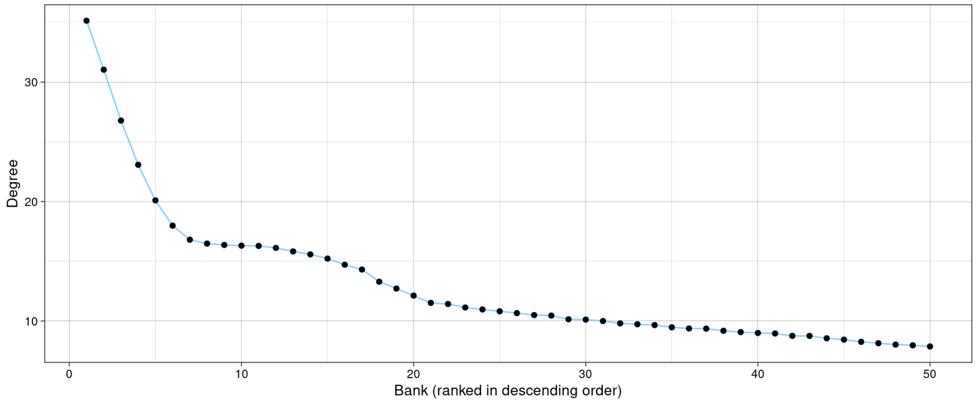
3. Simulations

To simulate missing data in a network, we add a link between two randomly chosen banks and compare the total loan repayments across the two networks. Our results come from network generation simulations that match observable network characteristics such as shape and degree distribution. Specifically, we calculate the repayment amounts of banks within the network when faced with an additional, previously unaccounted-for link.

We simulate financial networks in the following ways: We first generate a random network of loans that aligns with the observable degree distribution. We then find the repayment equilibrium as defined in Section 2. We then add a loan between two randomly selected banks that did not already have a loan between them. We then compare repayment equilibria between networks with and without the added link. We contextualize those results within aggregate economic outcomes. If we assume this new network with the additional link is the actual network, and the previous network represents the network that is measured, the disparity in repayment equilibrium can be interpreted as the result of missing data.

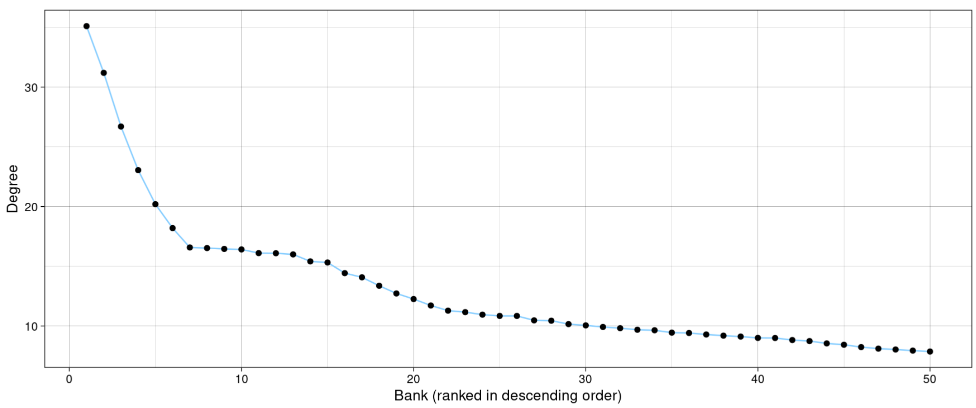
To generate random financial networks that match the degree distribution of the observed US financial network, we used a Python function called "powerlaw_cluster_graph" from the NetworkX package (Holme and Kim 2002). This package generates random undirected graphs that exhibit a specified degree distribution. In order to create a *directed* network, we generated adjacency matrices for two undirected networks and built the directed adjacency matrix from the top triangle of one undirected adjacency matrix and the bottom triangle of the other undirected adjacency matrix. This created directed networks that matched the specified power law distribution for the network degrees. The in-degree and out-degree distributions are depicted in Figures 2 and 3, respectively.

Figure 2: In-Degree Distribution



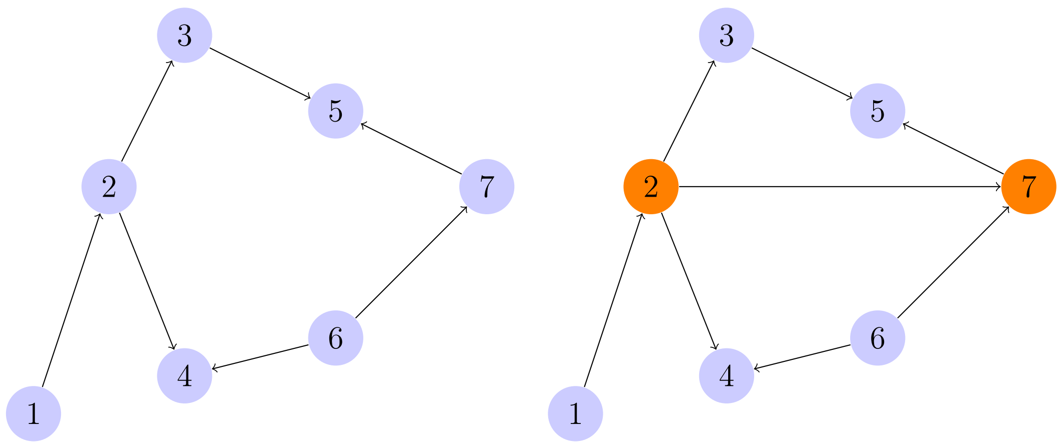
Notes: The in-degree distribution follows a power-law distribution.

Figure 3: Out-Degree Distribution



Notes: The out-degree distribution follows a power-law distribution.

We measure the total loan dollars that go unrepaid in each repayment equilibrium and refer to this as the "total shortfall" across each network. We calculate this for both networks and compare the difference between them. This metric is calculated by subtracting the equilibrium repayment amount for each loan between bank i and bank j, r_{ij} from the amount of money owed, y_{ij}.



(a) Network Before a Loan is Added (b) Network After a Loan is Added

Figure 4: Adding a Loan Between Two Banks

Notes: In the original network, there is no loan between Banks 2 and 7. In our simulations, the two banks we chose randomly would be Banks 2 and 7. In the second network, there is now a loan repayment due from Bank 2 to Bank 7.

We calibrate the model parameters to match observable characteristics. We generate random networks of 100 banks to match the degree distribution of the actual US Interbank lending network (Soramäki et al. 2007). The parameter values of the individual bank variables used in our simulations are described in Table 1. We calibrated the cash-on-hand value to match the total cash in vaults in US banks divided by the number of financial institutions (FRED: Federal Reserve Economic Data 2024). The senior obligations of the banks are set to the average wage obligations of US banks each month (IBIS World 2023). The random return on outside investments is drawn from a Normal distribution with a mean of 10 and a variance of 5, which can be interpreted as a mean of 10 million dollars and a variance of 5 million dollars.

Table 1: Parameter Values

Parameter	Value
Cash on hand (c)	15.9
Senior Obligations (v)	2.9
Return on Investment (A_j)	normal, 10, 5

We are restricted to simulations that consist of 100-bank networks for computational reasons.

The system of equations that defines the repayment equilibrium - as described in Section 2 - grows exponentially with the number of banks. It is computationally impractical to simulate networks with the full 4706 banks. In a network with n banks, there is the possibility of a loan between any bank and any other bank. This is the potential for $n(n-1)$ loans or links in the network, each of which would define a separate repayment equation. In a network with 100 banks there could be as many as $100(99) = 9,900$ non-linear equations in $9,900$ unknowns. We found that 100 nodes are the maximum number of banks that can run in a reasonable amount of time while still yielding meaningful results. A simulation of 500 repetitions with 100 banks takes approximately one week to run.

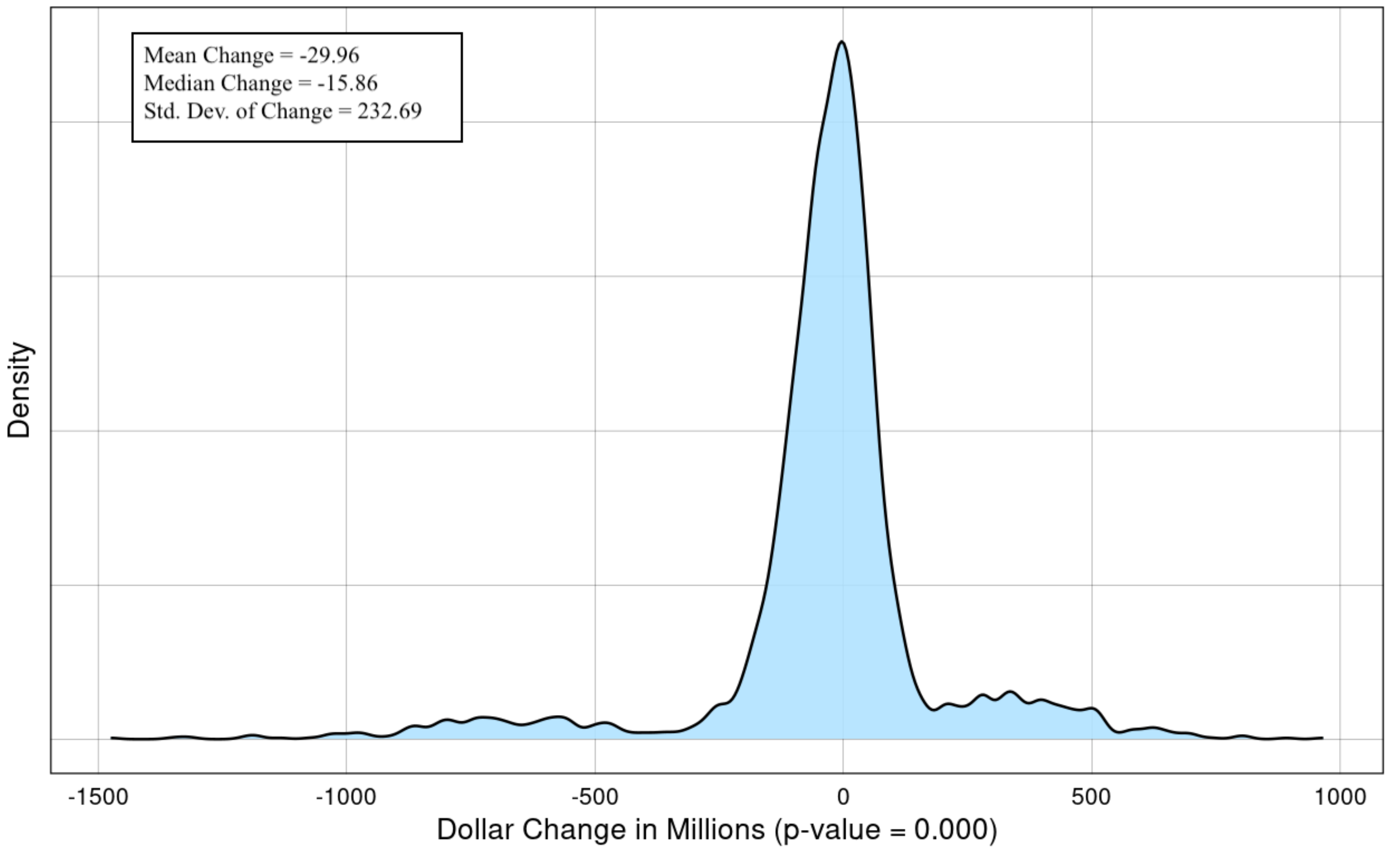
4. Results

Our simulations reveal that a minor change in the network structure, defined by the addition of a single link, results in substantial changes to network-wide repayments. We find that networks with an added link experience fewer dollars repaid than the equivalent network before the additional loan.

We ran 3,000 repetitions of a network experiment. We randomly generated a network with 100 banks, closely matching the degree distribution of the actual US interbank lending network. We calculate the repayment equilibrium on the network as defined in Section 2 and determine the total loan repayment shortfall across the whole network. We then add a link between two randomly selected banks and recalculate the repayment equilibrium and total shortfall. To ensure that the total shortfalls across each network are comparable, we subtract the repayment amount for the newly added loan from the shortfall calculation associated with the modified network. As a result, any change in shortfall amounts is due to the effect of the new link on other banks not the new link itself. Our outcome of interest is the difference between the total shortfall in loan payments between the two networks.

Figure 5 depicts the distribution of the effects of the added loan on total loan shortfall. On average, the network with the additional loans sees about \$29 million few dollars repaid. This difference is statistically different from zero (p-value = 0.000). That is, when the two lending networks are exactly the same except for a single loan, the total amount of loan repayments that are made across the network as a whole are statistically significantly different. Interpreted in the context of modeling, if we estimate the financial outcomes of a network that is only a little different than the real-world network, we could estimate significantly incorrect outcomes.

Figure 5: Difference in Unpaid Loan Dollars



Notes: Positive values indicate that the added loan resulted in less repayment, while negative values indicate higher levels of debt repayment

4.1. Bank Characteristics and Financial Outcomes

To better understand the role of individual banks on changes in aggregate network outcomes, we regress the measured change in total shortfall on a number of bank characteristics. Table 2 shows the results of these regressions. Specifically, we investigate the characteristics of the banks affected by the loan added to the network. Bank i lends bank j the additional loan, so bank j owes bank i 100 million dollars that it did not before. We examine the relationship between the randomly generated returns from other projects for both bank j and bank i, measured by A_j and A_i, respectively. We also include the in-degree and out-degree of both banks, i and j. Model 1 isolates bank i's contribution to the outcome variable. Model 2 evaluates only bank j's contribution to the outcome variable. Model 3 incorporates characteristics for both bank i and bank j.

Table 2: Regression Models of Simulations

Dep. Variable:		Network Shortfall	
Indep. Variable	(1)	(2)	(3)
Intercept	-67.4075^{***}	16.1210	-10.5114
	(12.0970)	(11.1341)	(14.5656)
A_i	-0.4690		-0.9304
	(0.8006)		(0.6973)
in-degree i	-14.0376^{***}		-15.1376^{***}
	(0.8492)		(0.7404)
out-degree i	16.1218^{***}		16.7838^{***}
	(0.8731)		(0.7607)
A_j		1.3470	1.2944^{*}
		(0.7561)	(0.6994)
in-degree j		20.8146^{***}	21.4845^{***}
		(0.8581)	(0.7944)
out-degree j		-23.3549^{***}	-23.9898^{***}
		(0.8398)	(0.7781)
Degrees of Freedom	2996	2996	2993
Residual Std. Error	220.3	207.4	191.8
Multiple R^2	0.1043	0.2064	0.3216

Notes: *p<0.1; **p<0.05; ***p<0.01; standard errors in parenthesis

The coefficients for the degree distributions are statistically significant predictors of change in network shortfall for each model. In Model 1, the coefficient for bank i's in-degree is negative. For every additional loan that bank i lends out, the resulting effect from the added link will change by 13.68 million dollars in the negative direction. The coefficient for bank i's out-degree is positive but similar in magnitude. For every additional loan that bank i borrows, the added loan results in a change of 15.59 million dollars in the positive direction.

The omission of a single link within the network significantly heightens the likelihood of overlooking a loan fully repaid, often involving substantial sums, amounting to tens of millions of dollars. Despite the ostensibly minimal nature of missing just one link, the disparities in outcomes can be considerable. The implications are particularly noteworthy in the context of crisis prediction. These results emphasize the necessity of identification and inclusion of network links to ensure accurate and precise forecasting.

5. Conclusion

This paper demonstrates the effect missing a single loan can have in the network of interbank lending. These small network differences can have large consequences. The addition of one loan can shift repayment equilibrium outcomes by hundreds of millions or even billions of dollars in either direction. This paper illustrates the importance of having perfect data on the entire network of interbank loans. If a difference of one loan can precipitate such a large swing in projected outcomes, having perfect data is all the more important. Correct policy decisions depend on our ability to understand the financial network. Imperfections in our understanding of the network could cause us to choose imperfect policy and wrongly project outcomes.

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