

Panic and Propagation in 1873

Daniel Ladley

Peter L. Rousseau^a

^aUniversity of Leicester School of Business, University of Leicester,
University Road, Leicester, LE17RH, UK

^bDepartment of Economics, Vanderbilt University, Box 1819, Station B,
Nashville, TN37235, USA

February 15, 2017

Abstract

Understanding the role of interbank credit relationships to systemic risk is challenging in that the total gross and net positions of banks can usually be observed from balance sheets but detailed information about particular correspondents is usually confidential. This was less the case for the United States in the early 1870s when the vast majority of banks were organized under national charters. The simpler portfolios held by banks at the time also render their balance sheets, which survive as recorded in the *Annual Reports of the Comptroller of the Currency*, more informative statements of condition than their modern-day counterparts. We use these advantages together with the regulatory constraints of the time to assess systemic risk in the U.S. banking system before, during, and after the Panic of 1873. We do this through a combination of linear programming and computational optimization that allows us to estimate the interbank network and utility parameters simultaneously using balance sheet data reported a week before the crisis. We show that,

consistent with historical observation, direct counter party risk was small, i.e., an unrealistically large shock would be needed for a significant number of banks to fail. Comparisons of the network for 1873, after imposing various liquidity shocks, with actual post-crisis balance sheets from the fall of 1874 show that the network can predict which banks became subject to panics.

Keywords: Panic of 1873, Reserve System, Crisis, Systemic Risk, Network.

JEL codes: G21, N11, N21, C63

1 Introduction

Understanding the susceptibility of financial systems to systemic risk, and in particular the contribution of interbank credit relationships to that risk, has taken on renewed urgency in the wake of the 2008 global financial crisis. With a few notable exceptions, however, analyzing actual interbank relationships presents a challenge given that the total gross and net positions of banks can usually be observed from balance sheets but detailed information about particular correspondents is usually confidential. Moreover, the rise of complex financial assets and increases in off-balance-sheet activities make it nearly impossible to assess risk based on financial statements alone. This was less the case for the United States in the early 1870s when the vast majority of banks were organized under national charters. This “National Banking System” experienced a panic and crisis in 1873 that shares key features with 2008, including credit shortages and system-wide stress driven by speculation in assets that turned out to be overvalued. At the same time, the simpler portfolios held by U.S. banks at the time render their balance sheets, which survive from the early fall of each year as recorded in the *Annual Reports of the Comptroller of the Currency*, more informative statements of condition than their modern-day counterparts. Less developed systems for the transfer of information and goods also made physical distance more important then for choosing interbank partners than it is now, i.e., while the internet and electronic market places now make it easy for banks to interact with any counter party in the world, this was not the case in 1873.

We use these analytical advantages together with the regulatory constraints of the time to assess systemic risk in the U.S. banking system before, during, and after the Panic of 1873. We do this through a unique combination of linear programming and computational optimization, with the services of a high performance computer cluster,¹ that allows us to estimate the interbank network and parameters of a given utility function for banks simultaneously using balance sheet data reported a week before the crisis. Using this network, we show that, consistent with historical observation, direct counter party risk

¹The final results presented in this paper take approximately 130,000 hours of computational time to calculate.

was small, i.e., an unrealistically large shock would be needed for a significant number of banks to fail. Indeed, losses from the New York banks that failed during the crisis played a secondary role compared to the liquidity shortages caused by spontaneous deposit withdrawals and their eventual effects on the distribution of interbank deposits across banks. Comparisons of our network for 1873, after imposing various liquidity shocks, with actual post-crisis balance sheets from the fall of 1874 show that our network predicts which banks became subject to panics with considerable accuracy. The results increase our understanding of a major historical crisis by demonstrating the robustness of the National Banking System as implemented, despite its apparent deficiencies, and point to the usefulness of network analysis in separating counter party risk from other systemic components when investigating disturbances in modern banking systems.

Our approach is deliberately broad in nature. Other recent studies (Calomiris and Carlson, 2016; Paddrick et al., 2016) using rich data on actual interbank balances from national bank examiner’s reports uncovered from the U.S. National Archives, offer insights on certain aspects of the network, but are not sufficiently complete or broad in geographic coverage or synchronized in timing to permit comprehensive analysis of a single systemic event. Paddrick et al. (2016), for example, study changes in interbank relationships and balances between 1862 and 1869 for banks in New York and for an incomplete set of their correspondents in Philadelphia and Pittsburgh, and in turn with those country banks that used the available Pennsylvania banks as redeeming agents. Our approach, in contrast, while not using specific pairwise interbank positions, analyzes the entire banking *system* of the time. We do this by exploiting the structure of reserve requirements and the gross interbank positions of all national banks between the fall of 1873 and 1874 to reconstruct a system of interbank linkages that, given the 1873 shock, accurately lines up with observed changes in aggregate interbank balances.

The crisis of 1873 was among the more serious under the National Banking System, which was in effect from 1863 until the founding of the Federal Reserve in 1913. The National Banking Laws created a new system to finance the Union effort during the Civil War by requiring that bank notes be secured with federal bonds rather than the

collections of assets that the states had previously accepted as collateral. Federal control of the collateral required to issue bank money was an improvement over the earlier system in which banks were granted charters by state legislatures or under state free banking laws. The National Banking laws included provisions that imposed a 10 percent tax on note issues of the existing state banks, which caused nearly all to either exit or convert to national charters by 1866, and created a Federal agency, the Office of the Comptroller of the Currency, to administer and provide oversight for the system.

The period leading up to the crisis can be characterized as one of general overbuilding in railroads financed by securities for which the risks were insufficiently understood by investors. The resulting balance sheet vulnerabilities among banks in New York City eventually led investors throughout the nation to re-evaluate their portfolios, and the failure of the investment bank Jay Cooke & Company on 18 September 1873 was the initial shock. Although Cooke was not a national bank but rather a private trust, its failure was followed by large withdrawals of individual and interbank deposits from several New York banks which, according to Sprague (1910, p. 15) were “directly responsible for the satisfactory working of the credit machinery of the country.”² Interestingly, these seven failures were the only ones in the nation to arise from the panic, yet the consequences on the distribution of deposits throughout the country turn out to be large.

2 Model

The analysis considers the network and distribution of interbank deposits among national banks before and after the 1873 crisis. In carrying out its monitoring role, the Comptroller required banks to periodically submit reports of their condition, and these reports provide the raw data for our analysis. In this section we describe these data and how they are used to estimate the interbank network.

²<https://fraser.stlouisfed.org/title/?id=56#!19089>

2.1 Data

Our networks are based on balance sheet data contained in the *Annual Report of the Comptroller of the Currency* for the years 1873 and 1874.³ The 1873 report includes data for all 1,976 national banks operating in the United States on 12 September 1873, while the 1874 report includes the 2,001 operating national banks on 2 October 1874. These banks account for more than 88 percent of bank capital in the United States in 1874.⁴ The first date occurs shortly before the failure of Jay Cooke & Company (Sprague, 1910), and offers a benchmark for the condition of the banking system before the event.⁵ The 1874 data are from the nearest reporting date a year later. The balance sheet data were collected using optical reading software and then checked by hand. Latitudes and longitudes of all banks were obtained using Google maps and measured at the geographic center of each municipality.

Each balance sheet includes information on a bank’s total interbank deposits. The liabilities side shows the value of deposits “due to national banks,” while the assets side lists deposits “due from other national banks” and those “due from redeeming agents.” Redeeming agents were themselves national banks located in designated “reserve cities,” which played a specific role in the regulatory mechanism.⁶ Banks outside of reserve cities were required to keep 15 percent of their customer deposits as cash, two thirds of which (i.e., 9 percent) could be kept as deposits at national banks in the reserve cities. The reserve city banks were themselves required to keep 25 percent of deposits as cash but half of this (i.e., 12.5 percent) could be kept in banks in the *central reserve city* - New

³<https://fraser.stlouisfed.org/title/?id=56#!19089>

⁴The rise of deposit banking and checking accounts made the issuance of notes less important as the 19th century progressed, and eventually fueled a resurgence of State banks outside of the National System after 1885, but there had already been some gains by 1874, with the number of State banks reaching 551 (or nearly 22 percent of the total). These state banks are not included in our network analysis, but were generally much smaller with an average of \$108 thousand of capital compared to nearly \$250 thousand for national banks (*Annual Report of the Comptroller of the Currency 1877*, pp. IV, XCI).

⁵Trusts were already an integral part of the financial system, especially in New York, and it is not surprising that a trust company was at the core of the initial shock. Given that there were only 35 trusts nationwide, all located in the Northeast and with an average capital of \$625 thousand, they could not have been a key element in the redistribution of national bank deposits that we examine here (*Annual Report of the Comptroller of the Currency 1877*, p. XCII).

⁶The reserve cities in both 1873 and 1874 were Albany, Baltimore, Boston, Chicago, Cincinnati, Cleveland, Detroit, Louisville, Milwaukee, New Orleans, Philadelphia, Pittsburgh, San Francisco, St. Louis and Washington.

York. National banks in New York City were then required to keep 25 percent of their deposits as cash. For non reserve city (i.e., “country”) banks, the “due from redeeming agents” item contains the total amount the bank had on deposit in reserve city and the central reserve city national banks, whereas for reserve city banks it represented the amount deposited in New York. For the New York City national banks, this value is always zero. It is these rules that provide the structure for the network model we describe below.

2.2 Building the Network

A bank that deposits funds in another creates a connection between the two institutions. Across the system these linkages form a network in which the nodes are banks and edges are interbank deposits. The balance sheets from the Comptroller’s reports include the total amount of interbank deposits held by and owed to each bank. Given that a comprehensive set of individual linkages in 1873 is not available, we build a representative network using the bank-level aggregates, regulatory structure, and a set of plausible bank utility functions for choosing correspondents and interbank deposit amounts.⁷

The Comptroller’s reports include the gross interbank positions of each bank but do not include the individual banks in which the interbank deposits are placed. The network

⁷For a network constructed from our data to be valid technically, the total interbank deposits held by a given bank must equal the “due to national banks” entry on the liability side of the balance sheet. Similarly the amount a bank keeps in reserve city banks and other banks must equal the sum of the amounts “due from redeeming agents” and “due from other national banks” on the assets side. By definition the total “due to” across the system should therefore be equal to the total of the “due from” values as every deposit appears as an asset for one bank and a liability for another. The data, however, do not quite conform to this standard, with the total asset position larger than the liability position by 2 percent. This likely reflects deposits being moved between banks. When funds are transported from a creditor to a debtor via non-instantaneous means it appears on the asset side of the creditor when it departs and on the liability side of the debtor only when it later arrives. If the money travels in the opposite direction it is removed from the debtors liabilities on departure and added to the creditors assets upon arrival.

We resolve this by scaling each bank’s interbank liabilities as follows:

$$L^j = L_*^j \frac{\sum_{i=1}^M (A_R^i + A_B^i)}{\sum_{i=1}^M L_*^i}, \quad (1)$$

where M is the number of banks, L_*^i is the recorded value of interbank liabilities of bank i , and A_R^i and A_B^i are the interbank assets due from redeeming agents and other banks respectively. The result is that total interbank liabilities are set equal to total interbank assets while preserving the relative sizes of these positions across banks. Valid interbank networks can then be constructed with the scaled data.

we construct can be viewed as estimating this missing information using a matrix where rows and columns are banks and entries correspond to specific interbank deposits. In this setting, the “due to national banks,” “due from redeeming agents,” and “due from other national banks” entries provide three constraints on the matrix entries for each bank. With diagonal entries zero by definition, a system with M banks would have $4M$ constraints to estimate M^2 variables, leaving the problem under-constrained for any network with $M > 4$ and therefore allow an infinite number of valid networks. Not all of these networks, however, are equally realistic. For example, a network could be constructed where each bank aims to place deposits in the most distant banks, yet the costs of transporting funds and gathering information would make such a network extremely unlikely in practice. Below we describe a set of constraints that produce more plausible networks.

To assess the likelihood of various networks, we model the banks’ utility function using three components. The first is distance. While wire transfers by telegraph began with the launch of Western Union’s service in 1872, they were costly and little used in 1873, and net settlements still required money to move physically by foot, horse, wagon, rail or canal, which entailed a cost. Distance also meant that banks would have less timely and thorough information about distant counter parties than for those nearby. These factors led banks to favor more proximate interbank partners. Such proximity effects persist in modern banking systems, for example, Degryse and Ongena (2005) relate transportation costs to price discrimination in recent loan markets.

We measure the distance between banks based on the the available transport routes in 1873. Maps of canals, navigable rivers and rail networks are taken from Attack (2013). We add sea routes by also creating a large number of possible routes between locations along coastal waters. We assume the existence of straight line roads traversable by horses, and while this is not completely realistic, the costs of land transport were so prohibitive that it was generally used for only short distances where the costs of a linear route would not differ much from actual. Travel times for each transport mechanism relative to horses are based on the speeds in Kaukiainen (2001). We identify the shortest distance between each pair of banks in the system using combinations of road, rail, canal, river and sea.

The second component affecting a bank's preferences is the financial soundness of the receiving bank. Since placing deposits in another bank entails credit risk, a bank may prefer to place deposits in a counterparty with a stronger balance sheet. There are numerous potential measures of financial soundness including capital and various financial ratios. Since specie comprised the ultimate form of liquidity in 1873, our main results use the amount on hand to represent balance sheet strength. Other measures were tested and yield similar networks.⁸

Finally, the banks in New York City holding the largest interbank deposits paid interest on these holdings, which made them more attractive as locations for surplus funds. Although we do not know the interest rates paid on interbank deposits by individual New York banks at the time, we can estimate the effect of paying interest when building the network through a third component in the utility function that can be thought of as reducing the economic distance between New York banks and any other banks in the system.

Let $F(i, j)$ be the utility of bank i placing a single unit of deposits in bank j :

$$F(i, j) = \frac{S(j)}{D(i, j)} \quad (2)$$

where $D(i, j)$ is a function of the distance in kilometers between bank i and bank j , and $S(j)$ is a function of the specie holdings of bank j . As such, bank i 's utility from making an interbank deposit is increasing in the specie and proximity of the recipient. Both $D(i, j)$ and $S(j)$ are of the form:

$$D(i, j) = (\log d_{i,j})^\delta \quad (3)$$

$$S(j) = (\log s_j)^\nu \quad (4)$$

where $d_{i,j}$ is the actual distance⁹ between banks i and j and s_j is the specie holdings of

⁸Other measures are similar but do less well at predicting how deposits are reallocated. I could put some of these in an appendix? Capital on the balance sheet, notes and coins, total assets.

⁹Banks in the same city are defined as having a small distance of 1 kilometer between them.

bank j . The δ and ν parameters control the shape of the utility function.¹⁰

If the actual interbank network were known, the values of δ and ν could be estimated to fit the data best, but this is not directly observed. We therefore use the available interbank aggregates to identify the most likely bank decision function and the optimal deposit network simultaneously. To estimate the network, we focus on those deposits mandated by regulation (i.e., the allocation of deposits of country banks to redeeming agents). Although country banks were required to hold deposits in reserve cities, there were no restrictions on which reserve city or reserve city banks (including those in the central reserve city) they could choose. We therefore evaluate the network based on the fit of interbank connections conducted through redeeming agents based on their soundness, distance, and desirability in terms of accruing interest for the depositing banks. In contrast, deposits among local country banks were based more on idiosyncratic choices or short-term liquidity needs.

To assess a given utility function we compare two allocations—with and without constraints. In the unconstrained allocation, each country bank places its deposits in the reserve city bank that yields the highest utility, i.e., the reserve agent for which $\frac{S(j)}{D(i,j)}$ is greatest. When calculated for all banks, this delivers an optimal distribution of deposits across redeeming agents for the given utility function and parameter values. Importantly, this distribution does not take into account the constraints imposed by the balance sheet data—in particular that the sum of deposits placed in a given bank must equal the value of “Due to national banks.”

In the constrained allocation, these “adding-up” restrictions are included when computing the network that maximizes total utility. If banks’ optimal choices of redeeming agents and allocation amounts in the constrained network differ from the unconstrained ones, this indicates that the utility function is not fully capturing bank behavior, i.e., the bank would prefer to place its deposits in a different redeeming agent but is unable to do so in the constrained case because that bank’s “capacity” had been absorbed by other banks. To measure this fit for a given parametrization, we calculate the mean squared error between allocations in the constrained and unconstrained allocations. If the utility

¹⁰More complex functional forms were considered, however, they had little effect on the results for example $\frac{\nu_1 S(j)^2 + \nu_2 S(j) + \nu_3}{\delta_1 D(i,j)^2 + \delta_2 D(i,j) + \delta_3}$

function perfectly captures bank behavior the two allocations would be identical, i.e., banks' unconstrained choices of redeeming agents would match those identified under the constrained network, producing a mean squared error of zero.

2.3 Implementation

We use a minimum distance estimation approach in fitting the model to the observed data. The distance is defined as the sum of the mean squared differences between the amount each bank would place in its preferred reserve city when unconstrained and the amount placed when constrained. We use numerical optimization with a grid search of the feasible parameter space to find the optimal δ and ν which minimizes this distance. A simple optimization reveals a highly uncorrelated parameter space (i.e., good solutions are not close together), which indicates sensitivity of the utility function to parameter choices. This is not due to the utility function itself, but rather to the highly non-linear nature of networks and their creation processes. Slightly different parameters can affect a bank's choice of where to place deposits, and as a consequence of the adding-up constraints, the optimal choices made by many others. In other words, even though the utility function retains its functional form, how precisely the various parameters lead it to rank individual pieces of information may differ slightly. To ameliorate the sensitivity, we repeat the optimization 100 times, adding each time a small amount of noise to the parameters δ and ν separately and independently for each bank, and then average across the runs.¹¹ This generates a smooth, correlated search space with a single minima.

Given a particular utility function, the creation of the optimal network becomes an instance of the linear transportation problem, which specifies a set of sources and sinks with known capacity. The sources and sinks are connected by links that have a cost for each unit transported along them. The problem is normally specified as one of cost minimization, but we convert it to one that maximizes utility. Sources are banks which act as interbank depositors, and their capacities are the amounts of interbank assets on

¹¹We search the grid in increments of 0.1 for both δ and ν . For each bank, we perturb each parameter by adding a value drawn independently and at random from $N(0, 0.02^2)$. We obtain similar results when all banks are given the same perturbation in each run.

their balance sheets. Similarly, sinks are receiving banks with capacities equal to their interbank liabilities. The cost of a link is the utility gained by the source bank for sending one unit of deposits to the connected sink. The solution to this problem is a network that maximizes total utility.¹²

In creating the network it is necessary to modify the utility function slightly to account for banks that are on average closer to other banks. If a network is created to maximize total system utility, banks situated closely to other banks, such as those in the northeast, will be favored, while little weight would be placed on the preferences of isolated banks, such as those in the northwest. This means that a northeastern bank may receive its first choice partner over a second choice with nearly equal utility, even if this results in a large relative reduction of utility for a northwest bank, so long as total system utility is increased. This can occur because distance enters into the denominator of the utility function, i.e., all correspondent choices have relatively low utility for distant banks, whereas differences of only a few kilometers can have large effects on utility for banks in the northeast. The shorter distances also mean these banks weigh more heavily in the system utility being maximized, thereby making the preferences of distant banks less important. To resolve this, we normalize each bank’s utility for placing deposits in a given bank by the sum of the possible utilities of depositing with all other M banks, noting once again that $F(i, i) = 0$:

$$\bar{F}(i, j) = \frac{F(i, j)}{\sum_{k=1}^M F(i, k)}. \quad (5)$$

Normalizing utility in this manner treats each bank’s preferences as equally important in the allocation, and the $\bar{F}$ values now correspond to the banks’ relative preferences.

¹²A bank may be both a depositor and receiver of interbank funds, and to prevent the algorithm from having a bank place deposits in itself (the shortest distance), the utility of these links is set to zero. Similarly, a bank may have both reserve city deposits and non-reserve city deposits, as shown by separate listings on the balance sheet. In this case we map the bank to two sources—one with capacity equal to the ‘Due from redeeming agents’ entry, which has zero utility for connecting to non-reserve city banks, and a second with the ‘Due from other national banks’ entry, which has zero utility for deposits in reserve city banks. After identifying the optimal network these sources are then recombined to form a single bank.

3 The Pre-Crisis Network

3.1 Choice of Reserve Agents

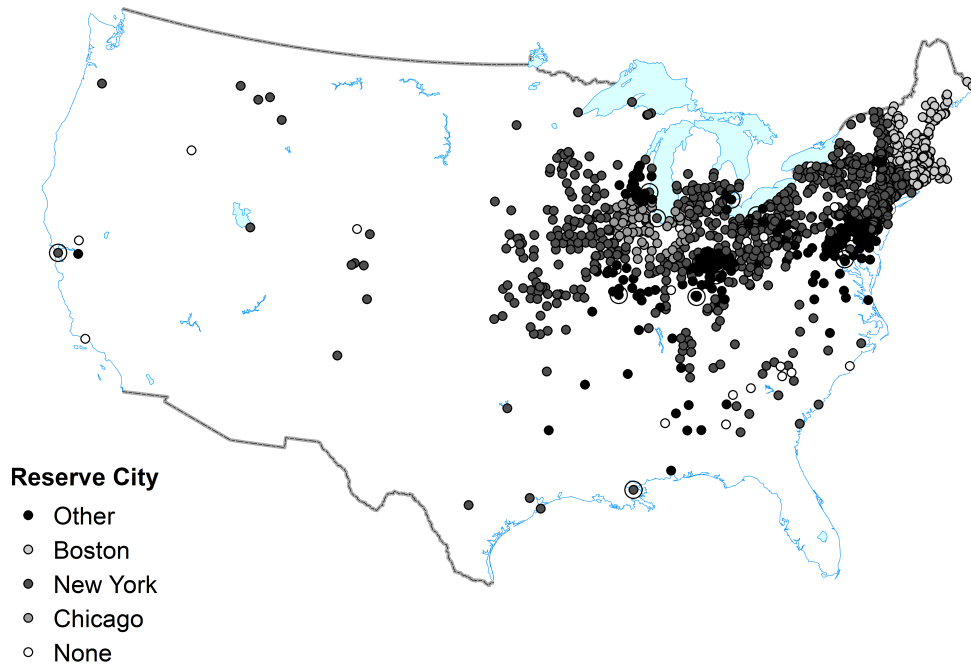


Figure 1: The graphs shows for each bank the reserve agent in which each bank places the majority of its deposits. Results are from a single simulation of the model and are representative of other simulations.

Using balance sheet data for all national banks from 12 September 1873, we compute the optimal parameter values of ν and δ to be 1.2 and 0.7 respectively. Figure 1 shows the primary reserve agent for each bank as computed by the network algorithm and rules for a single Monte Carlo simulation. The primary reserve agent is the agent in which a given bank places the most deposits. We present this example for a single simulation rather than an average over multiple simulations to show the geographical mix of choices that the network can spawn rather than modal choices, which tend to overstate the number of banks that would have placed deposits in New York. The darker shades denote banks placing deposits in New York, Chicago, and Boston, while the lightest shade marks banks depositing in other reserve cities. Figure 2 offers a closer view for the mid-Atlantic area, where banks depositing in Baltimore, Philadelphia, and Washington,

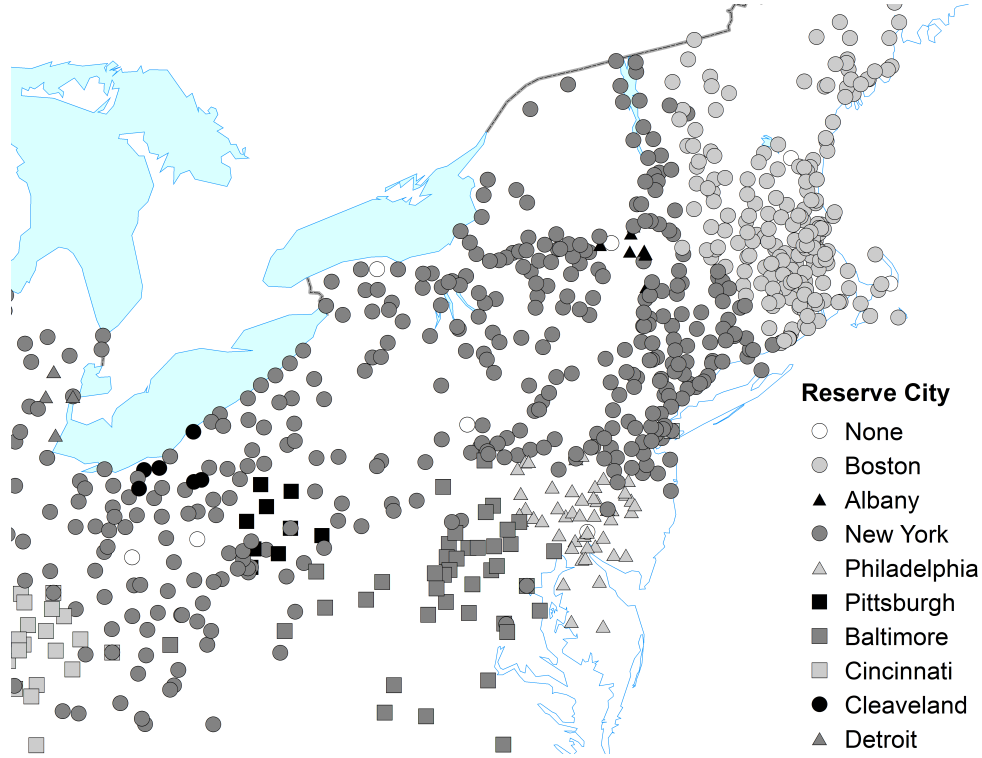


Figure 2: The graphs shows for each bank in the Atlantic North East the reserve agent in which each bank places the majority of its deposits. Results are from a single simulation of the model and are representative of other simulations.

DC can be distinguished. Although the graphs do not allow us to show all banks in the various clusters due to their density and overlap, the key finding is that banks near a reserve city tend to use banks in that city as the primary reserve agent, but that the geographic breadth of each reserve city is based on a combination of specie reserves, distance from other reserve cities, information costs, and the density of banks in the region. The exception is New York, which was a popular reserve agent for country banks from all regions, including banks in locations far from any reserve city.¹³

Figure 1 also shows that the various reserve cities primarily place deposits in New York. The clearest cases for observing this are Chicago, New Orleans and San Francisco.

¹³This latter result occurs because distance is less important to the optimal choice of reserve agent for an isolated bank given that all reserve agents are relatively far away. This makes specie on hand, for which the New York banks generally held the most, the primary determinant of correspondent choice.

3.2 Stability

We now consider the probabilities of bank failures spreading through the interbank market. Our network offers a mechanism whereby losses at a bank may leave it with insufficient funds to redeem interbank liabilities, causing its counterparties to also incur losses. Since the 1873 crisis originated in New York City, we simulate the losses that occur when the balance sheet value of loans made by New York banks are reduced by some arbitrary percentage R , and then vary R to compare the magnitude of losses and incidence of failure in each case. At this point we focus solely on bankruptcy caused by interbank defaults, and turn to insolvencies later.

We assume that banks have sufficient equity to repay the deposits of creditor banks if their own interbank assets are repaid. In addition, each bank has capital and possibly undivided profits and a surplus fund to absorb losses before they fall upon its creditor banks. If funds are insufficient, losses are divided among the interbank depositors in proportion to their deposits with the troubled bank. Note in this case we deliberately make strong assumptions about the propagation of crisis: Banks must repay their own deposits immediately and all losses beyond equity are constrained to interbank depositors. Similarly we do not model the effects of clearinghouses within the system, which would also act to reduce losses. Despite these assumptions, as we will show below, the system is very stable.

To compute the effects of losses in New York, we employ the algorithm of Eisenberg and Noe (2001). This approach identifies a unique and feasible set of interbank payment flows. We set the required payments equal to those calculated by the network. Each bank has external resources $e_i = Capital + SurplusFund + Profits - LoanLosses + DepositsDueFromBanks - DepositsDueToBanks$. The final two terms, as previously noted, ensure that the bank has sufficient funds to make its payments if their own deposits are repaid, and correspond to the payments the banks will make to and receive from other banks - both redeeming and non redeeming. Loan losses are zero in this instance for all banks outside of New York, and are Rl_i for any New York bank i , where l_i is the amount of loans on bank i 's balance sheet. The Eisenberg and Noe algorithm iteratively calculates

the set of payments made between banks until a fixed point is reached. This problem itself is not trivial due to the potential for cycles within the interbank market and the requirements that losses are divided proportionately among creditors and that no bank makes payments greater than its available resources.

3.3 Propensities for Bank Failure

Figure 3 shows the number of banks that fail across the financial system for different magnitudes of the shock R . The smallest shock that causes bank failures is 30 percent. In this case on average approximately eight banks fail in total, five of which are located in New York. The effect propagates more deeply through the system as we increase R . For small shocks (under 40 percent) most failures are limited to New York. For intermediate shocks (40%-70%) the majority of failures are in reserve cities, while for larger shocks the most failures occur among the country banks. Larger shocks deplete increasing amounts of equity, leading to waves of failures, but it is only for very largest shocks that reserve banks are unable to absorb losses and their failures in turn cause large numbers of country banks to fail. In extremes approximately 22 percent of banks in the system may fail, including approximately 63% of reserve city banks and 64% of those in New York. These results suggest that the banking system was highly interconnected in 1873 and that an enormous shock would have been required in New York to cause extreme damage. Yet in 1873 the size of the shock was nowhere close to this, and as such, inline with our findings, failures were very few.

Figure 4 shows how reserve bank failures are distributed. It can be seen that New York bears the brunt of failures at intermediate levels of R , with 54% of banks failing, but as shocks increase Chicago accounts for approximately the same percentage of failed banks albeit with a much lower absolute number. Boston, Albany, Philadelphia, Washington, Baltimore, St. Louis and Pittsburgh also begin to suffer considerable numbers of failures, in the range of 30 to 40 percent of banks by the time R rises to 70 percent, while banks in other reserve cities remain relatively unaffected.

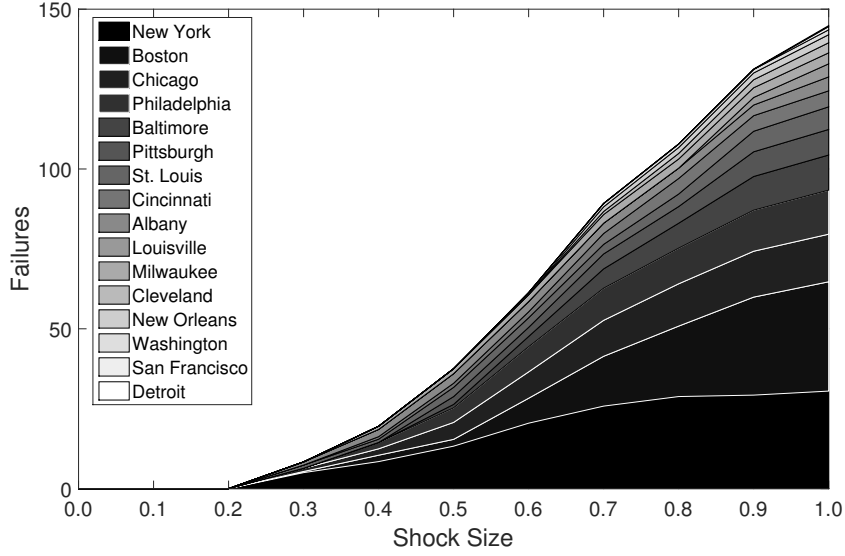


Figure 3: The average number of banks that fail in the financial system broken down into New York Banks, Reserve City Banks and Country Banks, in response to shocks to a fraction of loans in New York banks varying between 0 and 1 in steps of 0.1. For each point the results are averaged over 100 different inter bank networks.

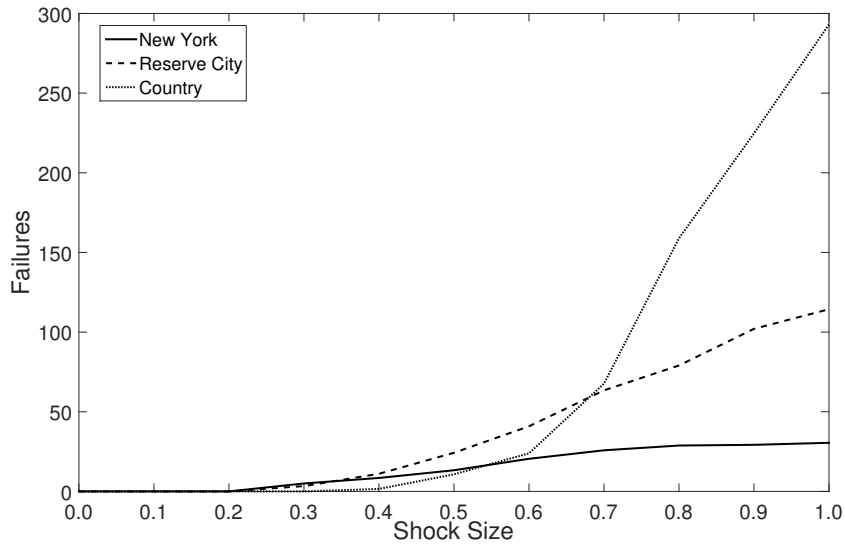


Figure 4: The average number of banks that fail in each reserve cit (including New York), in response to shocks to a fraction of loans in New York banks varying between 0 and 1 in steps of 0.1. For each point the results are averaged over 100 different inter bank networks.

4 Fit of Model Predictions to 1874 Data

In this section we subject the optimal network formed with the data from 12 September 1873 to a set of structured withdrawals, and compare the results to the observed

distribution of interbank deposits on 2 October 1874.

4.1 Withdrawal Patterns and Processing Rules

We consider the following nine scenarios:

1. No withdrawal by any bank leaving the distribution unchanged. This serves as a baseline for the affect of shocks.
2. All banks reduce their interbank deposits by an equal percentage α_1 .
3. All banks reduce interbank deposits, but the extent to which they do depends on the distance of their counterparties from New York. In other words, a given bank's correspondents further from New York see their interbank liabilities reduced less than those correspondents nearer to New York. This allows for the possibility that depositing banks become concerned about linkages between their own counterparties and the New York banks, which were the original source of the crisis. Interbank positions are reduced by $f(i)$ where $f(i) = \alpha_2(1 - \beta_2 \frac{d_i^{NY}}{\max_j d_j^{NY}})$, and d_i^{NY} is the distance between the deposit receiver and New York.
4. All banks with deposits in New York withdraw a fraction of their funds. This simulates a more concentrated shock where only those banks with credit balances in New York withdraw a share α_3 of their interbank deposits.
5. The same withdrawal as 4 but with an additional reduction in the interbank deposits of all banks α_5 analogous to 2.
6. The same withdrawal as 4 but with an additional reduction in interbank deposits by all banks dependent on the receiving bank's location in a manner analogous to 3.
7. All banks with interbank deposits in New York withdraw a fraction α_4 of their funds and place them in other reserve city banks. This once again simulates a concentrated panic, but this time banks outside of New York remove a share α_4 of any New York

deposits and place them at presumably safer agents in other reserve cities, with the reallocation maximizing their utilities as defined by the network.

8. The same withdrawal and reassignment as 7 but with an additional reduction in the loans by all banks of α_5 in a manner analogous to 2.
9. The same withdrawal and reassignment as 7 but with an additional reduction in the loans of all banks dependent on the receiving banks' proximity to New York in a manner analogous to 3.

For each of these shocks, we numerically find the α and β parameters that minimize the mean of the squared errors at the county level between the 1874 data and the interbank balances generated by propagating the shock through the network we constructed for 1873. Since many banks make small changes to minimize the countywide error under the algorithm, which likely differs from changes that would be observed in practice, the results are best thought of as a probability distribution, i.e., the probability that a bank will respond in the manner predicted by the model.

4.2 Qualitative Results

Figure 5 shows the actual reduction in interbank deposits between the Comptroller's reports of 1873 and 1874, aggregated at the county level. Decreases appear in shades of red while increases are in shades of green. Yellow counties see little or no change, and non-shaded counties represent those without banks. The map shows that the majority of reductions occurred in the northeast, and particularly in the areas surrounding New York City. New York itself suffers a large reduction of \$6 million, which is about 10 percent of its interbank holdings. Reductions are generally smaller and more isolated in other parts of the nation, but there are significant reductions in some counties – in particular those corresponding to the reserve cities of Cincinnati, Philadelphia and Pittsburgh. At the same time, there are many counties that experience increases, including the reserve cities of Chicago, which gain more than \$1 million, and Detroit, Louisville and San Francisco, which gain between xx, xx, and xx respectively. \$100,000 and \$500,000. Figure 6 provides

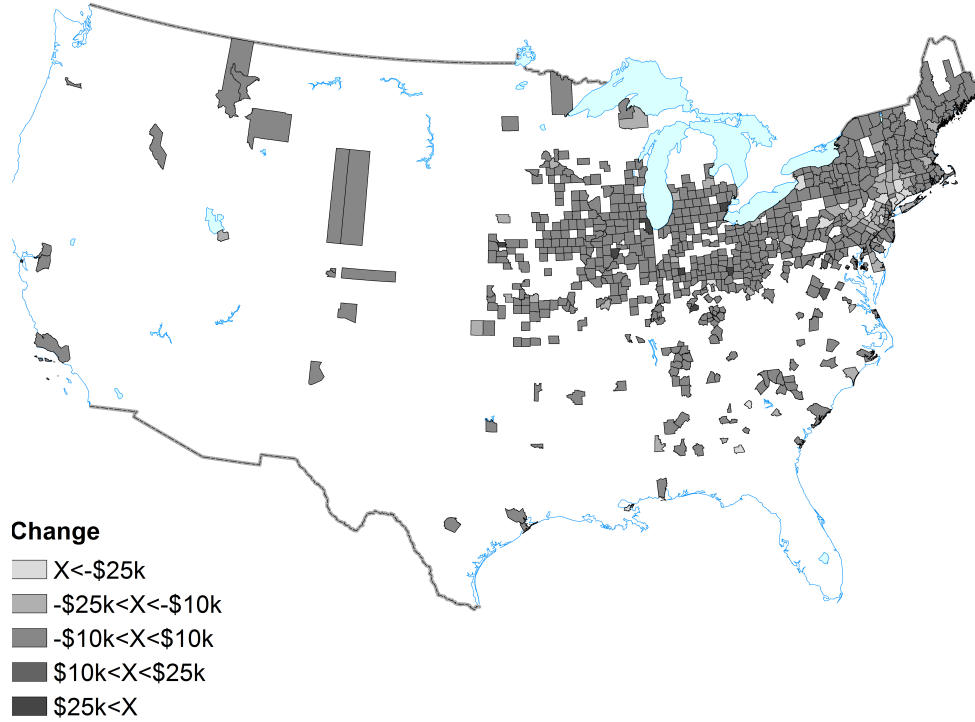


Figure 5: Changes in levels of inter bank deposits as measured by ‘Due to Other National Banks’ entries in Comptroller of the Currency Reports. Data are aggregated at the county level and the difference between the 1873 and 1874 data are shown across the country.

a closer view of the northeast, which highlights that the majority of counties in the area see large reductions, including the reserve cities of Albany and Baltimore. Boston is an important exception, however, with interbank deposits rising by more than \$4 million, which represents the largest increase of any county over the one-year period.

With the exception of the geographic concentration around New York, there are no other clear patterns or indications of the mechanisms driving the changes in deposits. In the following section we compare the changes in the data described above with our network model of the crisis to understand how changes in the distribution of interbank deposits could have occurred.

4.3 Quantitative Results

The mean squared error, presented in Table 1, provide a similarity measure between the 1874 data and the distributions of interbank deposits when the nine cases described above are applied to the 1873 data. Case 2 is the simplest withdrawal; a flat reduction of inter

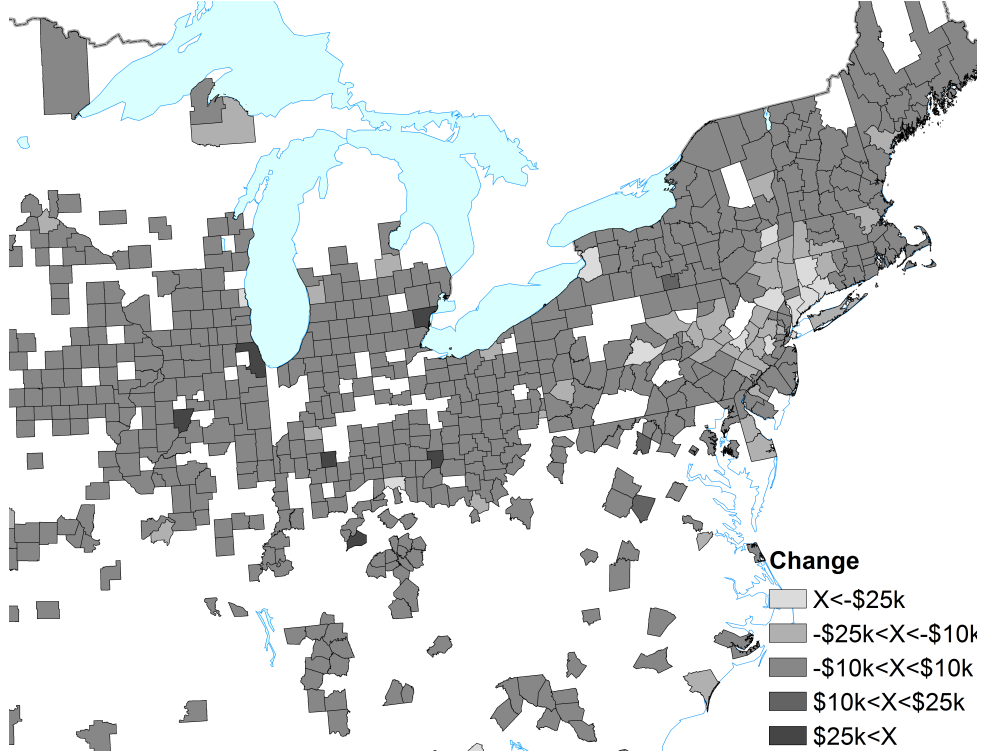


Figure 6: Changes in levels of inter bank deposits as measured by ‘Due to Other National Banks’ entries in Comptroller of the Currency Reports. Data are aggregated at the county level and the difference between the 1873 and 1874 data are shown for the north east mainland.

bank deposits across all banks, ignoring the identify of the depositor, the deposit receiver, and their locations. The optimal value of α_1 was found to be 0.09. A withdrawal of this magnitude reduces the error by approximately 61% relative to the “no withdrawal” base case. This flat withdrawal results in a more accurate matching between the model and empirical data. It indicates that the system lost approximately 9% of its inter banks deposits during this crisis. While it significantly reduces the error, this pattern of withdrawal is not able to account for the increases seen in some reserve cities in the data.

Case 3 models a more sophisticated withdrawal. In this setting, banks close to New York are judged to be more at risk of failure than banks further away. This is based on the hypothesis that banks close to New York may be exposed to the possibly more risky investment practices of New York banks than those further away. This exposure may either be direct, through making the same investments, or indirect, through connections to exposed banks. The gradient functions allow us to model this type of withdrawal and to capture a further 1.4 percent reduction in the error with parameters $\alpha_2 = 0.1$ and

Scenario	Squared Error
1	8.57
2	3.38
3	3.26
4	2.24
5	2.15
6	2.14
7	1.68
8	1.49
9	1.48

Table 1: Table showing the similarity between the model data sets and the distribution of loans in 1874. Results are shown for each of the scenarios described above. The correlation and error are calculated based on the difference between the ‘Due to National Banks’ entry on the 1874 data and the model output for all counties with one or more banks. Error is defined as $\sqrt{\sum_{i=1}^N (D_{1874} - D_{Model})^2}$ where N is the index over counties, D_{1874} and D_{Model} are the ‘Due to National Banks’ values of the historical and model data.

$\beta_2 = 1.0$. The size of the effect, however, is an order of magnitude smaller than the flat reduction considered in case 2. As such, while banks may have viewed those close to New York as more exposed to the crisis, it had relatively little effect on behavior.

The third case, 4 models a withdrawal from New York by those banks using it as a reserve city without withdrawals from any other banks. The scale of this withdrawal is not optimized to maximize the reduction in error, instead it is set equal to the empirically observed withdrawal from New York. This withdrawal, targeted at those banks connected to New York results in a reduction in error of 74%. The application of a further withdrawal of 1%, case 5, reduces the error by a further 1%. A distance based withdrawal - case 6, however, has a negligible effect (4th significant figure). As such we may say that the network withdrawal captures this effect.

If non-reserve city banks reallocate their withdrawn reserves to other reserve cities - case 7 (banks in reserve cities do not reallocate - instead they keep them in their own city) the model’s fit improves significantly. This withdrawal and reallocation reduces the error from the base case by 80% an improvement of 6 percentage points over the non-reallocation case. Even though no reserves are withdrawn from the system, the reallocation from New York to other reserve cities matches the empirically observed distribution closely. In particular, the model now matches the actual increases observed for Chicago, Boston and

Detroit. This shows that reserves were withdrawn from New York by those banks which were inter bank depositors and placed in other reserve cities, and this behavior resembled the utility function specified previously. Importantly it was not the behavior of banks in reserve cities that were driving this dynamic as these banks did not reallocate their funds. Instead it was the country banks who were moving funds out of New York and placing them in Chicago, Boston and Detroit. Without the use of the network it would not have been possible to theorize about those banks depositing in New York and therefore to identify where they might have reallocated their funds.

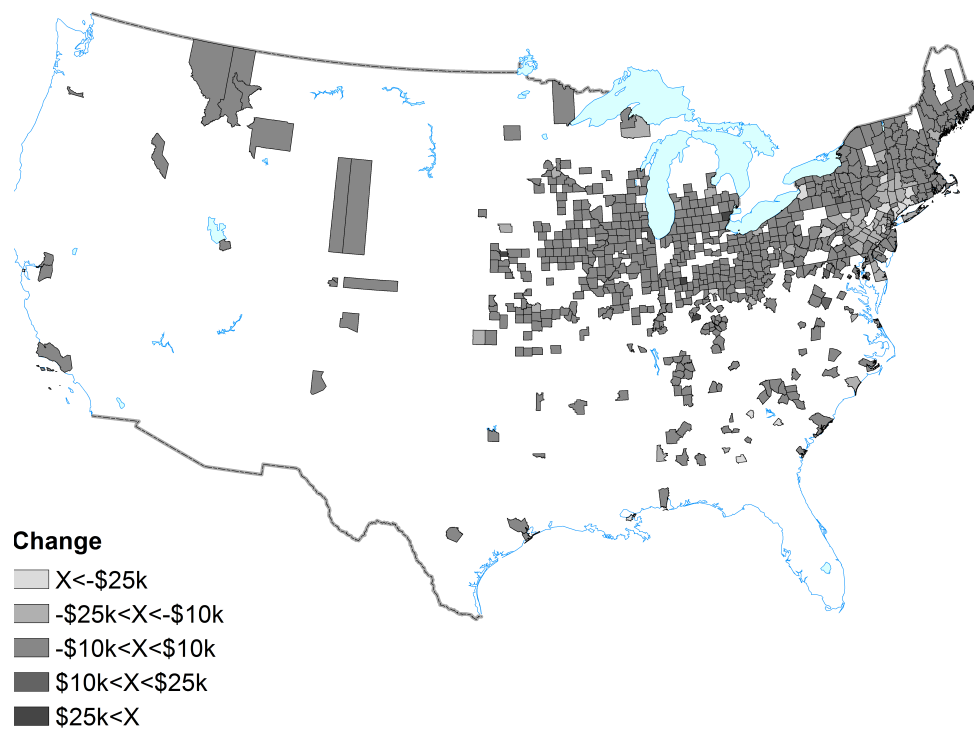


Figure 7: Diff in diff graph comparing the changes in the ‘Due to Other National Banks’ entries in Comptroller of the Currency Reports between 1873 and 1874 and a similar change within the model after the shock. Data are aggregated at the county level. Positive values indicate the model underestimated. PETER: These values are averages per bank under/over shoots I also have one that does a sum at the country level but prefer this as it doesn’t punish big counties to the same degree.

Case 8 looks at the effect of a uniform reduction in inter bank deposits for all non New York banks. The effect of a withdrawal of 2% is to reduce the error by a further 2%. This indicates that while there were some general reductions in inter bank positions between county banks, the effects were small in magnitude compared to the effect of

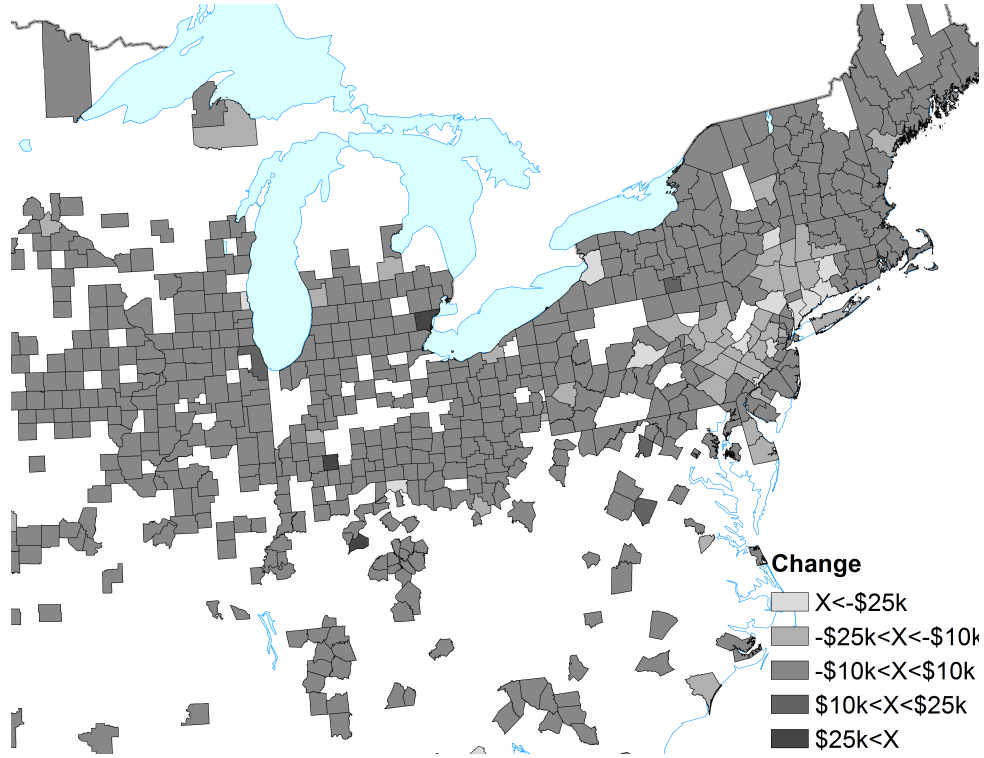


Figure 8: Diff in diff graph comparing the changes in the ‘Due to Other National Banks’ entries in Comptroller of the Currency Reports between 1873 and 1874 and a similar change within the model after the shock. Data are aggregated at the county level. Positive values indicate the model underestimated. Graph focused on the North East. PETER: These values are averages per bank under/over shoots I also have one that does a sum at the country level but prefer this as it doesn’t punish big counties to the same degree.

reserves being moved out of New York to other reserve cities. Figures 7 and 8 show the changes in inter bank positions under this shock. It can be seen that for the vast majority of counties their error is very small. In only a very few counties is there a significant deviation. The mechanism captured by case 7, where by banks move their deposits from New York to other reserve cities, leads to deposits in the reserve cities coming close to the actual data. The general withdrawal modeled by case 8 additionally captures the effect for other counties. The use of a more complex gradient-based model of withdrawal, as considered in case 9 again has a negligible effect on the results. This may be contrasted with case 3 where the gradient function led to a further reduction. In this case the withdrawal from New York has already occurred due to the reserve reallocation. The gradient-based model of reallocation does not capture the observed behavior beyond this and so may be discounted as an explanation.

5 Predicting Banks that Panicked

In this section we test the validity of our network by considering the events necessary to transition between the distribution of deposits in 1873 and that of 1874. We do this by finding the minimal set of banks that would have changed reserve agent in order for interbank deposit levels to match at the county level. A bank that changes reserve agent can be considered as one that “panicked” in response to the crisis and relocated deposits to more desirable counterparties. Our 1873 network predicts specific banks that would have switched redeeming agent, and a comparison of how well the model lines up with actual changes in geographic balance quantities provides a test of the model.

5.1 Algorithm

1. The algorithm commences with the 1873 network
2. Each bank’s interbank positions are scaled by $\frac{1874PositionSize}{1873PositionSize}$
3. For each bank the utility of placing its reserve deposits in each reserve city is calculated
4. The banks utility change for moving its deposits form it’s current reserve city to each other reserve city are calculated
5. Banks are ranked in order of potential utility improvement for moving deposits
6. Starting with the largest potential utility improvement each banks in the list has it’s deposits switched as long as the reserve city it is switching to has too few deposits in 1873 relative to 1874 and the reserve city from which it is switching has too many. Each bank may only move it’s deposits once. If the change in deposits would take the new county over the 1874 total or the old county under only a fraction of deposits are moved such that this is not the case.

We apply this algorithm to each of the 100 networks generated above in order to identify those banks most likely to change reserve agent and which reserve agent they move to.

5.2 Changes in Reserve Agents

Table 2 indicates which banks changed their reserve agent between 1873 and 1874. It includes new banks in the case of which bank they selected. The results are broadly sensible. We see that banks which gained tended to attract geographically close banks whilst those that lost, in particular New York, lost banks to near neighbors. Boston is interesting because it attracts new Depositing banks from further away - in particular it capitalizes on New York's losses.

We can use the set of banks found above who change their counter party to describe those banks who 'panic' in the crisis. We may then look at the change in balance sheets data between 1873 and 1874 for these banks to see if there is evidence that they differed materially from other banks. For this part of the analysis we exclude all reserve and central reserve banks and focus on only country banks. We compare balance sheet statistics of those that changed reserve agents with those that did not. Results are below:

The results above give a very clear picture. Those banks which the model predicts will have panicked reduce their loans by a greater degree - indicating that they are less willing to lend and take risks. They reduce their inter bank deposits by a greater degree indicating they believe there is more credit risk. This is particularly focused on reserve agents who may be believed to be riskier. They increase their specie holdings by a greater degree. This also fits our story of banks seeking specie. They make lower profits in this period -panicking costs them money. Both types of banks see a fall in deposits placed in them, however, for the average bank this falls much more for those panicking banks - they were seen as less risky due to their changes

In general these results are very strong and a very good supporting point for the model. In essence we have used inter bank balance plus our theory of how inter bank deposit decisions are made to generate a set of banks who we think will have changed reserve agent during the crisis. We have then looked at the balance sheet of these banks - in particular at (in nearly all cases) data which is not in the model e.g. loans, assets, specie and what we see is what we would expect. This indicates that the model is working well. Another way to say this is that we see an effect (a net change in deposits) and use

Reserve	Bos.	Alb.	N.Y.	Phi.	Pit.	Bal.	Was.	N.O.	Lou.	Cin.	Cle.	Chi.	Det.	Mil.	St.L.	S.F.
Boston	343.26	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Albany	7.76	10.45	0	0	0	0	0	0	0.27	0	0	0	0	0	0	0
New York	47.22	0	1002.2	0	0	0	0	0	2.38	0	0	0.01	7.01	0	0	1.59
Philadelphia	0.06	0	0	66.26	0	0	0	0	0	0	0	0	0	0	0	0
Pittsburgh	0.26	0	0	0	3.84	0	0	0	7.87	0	0	0	0	0	0	0
Baltimore	23.33	0	0	0.2	0	33.97	0	0	1.92	0	0	0	0	0	0	0
Washington	4	0	0	0	0	0	1.34	0	0	0	0	0	0	0	0	0
New Orleans	8.91	0	0	0	0	0	0	5.3	0	0	0	0	0	0	0	1.32
Louisville	0	0	0	0	0	0	0	0	9.25	0	0	0	0	0	0	0
Cincinnati	0	0	0	0	0	0	0	0	6.39	64.02	0	0	0	0	0	0
Cleveland	2.48	0	0	0	0	0	0	0	4.85	0	1.08	0	0	0	0	0
Chicago	0	0	0	0	0	0	0	0	0	0	0	93.1	0	0	0	0
Detroit	0	0	0	0	0	0	0	0	0	0	0	0	6.65	0	0	0
Milwaukee	2.47	0	0.01	0	0	0	0	0	0.2	0	0	7.84	0	8.03	0	1
St. Louis	8.32	0	0	0	0	0	0	0	0	0	0	2.95	0	0	13.24	0.1
San Francisco	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2.29

Table 2: Table showing the average amount of banks changing between each pair of reserve agents. Diagonal values are those that don't move.

Group	Due from		Due from		Undivided		Due to	
	Loans	Reserve Banks	Other Banks	Specie	Assets	Profits	Other Banks	
Changed	-2.74%	-21.14%	-15.15%	53.52%	-0.85%	-0.05%	-33.75%	
Not Changed	-1.57%	-16.84%	-14.64%	0.88%	-1.32%	1.63%	-39.61%	

Table 3: Table showing the percentage change in the median balance sheet values of those banks who changed reserve agent and those banks who did not between 1873 and 1874. There are 152 panicking banks and 1556 non-panicking.

the model to generate who made these changes and the prediction is correct.

6 Conclusion

We use a new computational approach to study the interbank deposit network in the United States around the Panic of 1873, simultaneously estimating both the most likely network and the utility functions of banks at this time. The resulting network is resilient to direct contagion with only small numbers of banks failing in response to shocks - similar to that observed historically. The network was shown to provide a more accurate model for the withdrawal of funds after the shock than was possible using bank locations alone. The fit was further increased if the model were used to reallocate funds after the withdrawal. Finally the model was used to identify those banks most likely to have panicked during the crisis from the resulting reallocation of interbank positions. Examination of exogenous data of those predicted to panic was consistent with this story. The results of this paper provide a clear separation between the relatively small direct effects of the crisis and the much larger informational or fear based panic. As such this paper increases our understanding of these two interrelated concepts and additionally opens a potential new research approach to understanding other crisis both past and future.

A Robustness

In this appendix we consider a number of additional sources of information and frictions which may further refine the network.

A.1 Redeeming Agents

The Bankers Almanac in the early 1870's provide a list of the 'New York Redeeming Agent' for each National Bank. Banker's Almanac data are available for December 1872 and March 1874. Both lists were manually inputted and the listed redeeming agents matched to banks in the Comptroller sample where appropriate. Despite being described as the New York Redeeming Agent, the banks listed were in many cases not in New York

- there are many instances of banks in Boston, Philadelphia and Pittsburgh being named. Many name multiple banks as Redeeming Agents (the maximum being three). Whilst several banks name private banks as either their sole redeeming agents or one of a group. There are relatively few changes between the 1873 and 1874 lists with the exception of those banks who used Jay Cooke and Co. as Redeeming Agent.

The redeeming agents listed in the Bankers Almanac represent knowledge of existing relationships. They do not, however, necessarily mean that reserves are kept in these banks. The existing relationships, however, imply that these banks are closer in information space than their physical distance would imply. We therefore incorporate this knowledge by reducing the distance between every bank and its listed redeeming agents by some value $1.0 - \theta_R$. We optimize θ_R at the same time as δ and ν using the same process as described above and find that the optimal value is $\theta_R = 1.0$. This information therefore does not improve the fit of the model. This is because with a few exceptions the set of banks used as redeeming agents is relatively small meaning that those banks would be overly favoured by this scheme and so attract too many deposits.

A.2 Interest on Deposits

One of the reasons that deposits were placed in New York banks as opposed to more local reserve agents was that these banks paid interest on interbank deposits unlike those in any other city in the United States. The New York banks were able to do this by lending the reserve cash to investors who in turn speculated on railroad bonds. This interest potentially creates an additional attraction for non New York Banks to place their deposits in New York.

This effect can be modeled by reducing the distance between New York banks and any other bank in the system. If distance is thought of as a physical space with an associated cost of travel, interest paid on deposits effectively reduces this transportation cost. Distance between banks and New York banks are reduced by $1.0 - \theta_I$ where θ_I is optimized along with δ and ν by the same process as described above. We find that the optimal $\theta_I = 0.95$ (to the nearest 0.01) meaning that interest payments do have an effect

on banks' decision making function. The affect, however, is relatively small - overall fit between the network and real data increase by approximately 2% The remaining results are qualitatively similar as those presented above and are available upon request.

References

- Atack, J., 2013. On the Use of Geographic Information Systems in Economic History: The American Transportation Revolution Revisited. *The Journal of Economic History* 73 (02), 313–338.
- Boyd, J. H., Walton, Gary, M., 1972. The social savings from 19th century rail pannenger services. *Explorations in Economic History* 9 (3), 233–254.
- Calomiris, C. W., Carlson, M. A., 2016. Interbank networks in the national banking era: their purpose and their role in the panic of 1893. Tech. rep., Columbia University.
- Degryse, H., Ongena, S., 02 2005. Distance, Lending Relationships, and Competition. *Journal of Finance* 60 (1), 231–266.
URL <https://ideas.repec.org/a/bla/jfinan/v60y2005i1p231-266.html>
- Eisenberg, L., Noe, T. H., February 2001. Systemic Risk in Financial Systems. *Management Science* 47 (2), 236–249.
URL <https://ideas.repec.org/a/inm/ormnsc/v47y2001i2p236-249.html>
- Kaukiainen, Y., 2001. Shrinking the world: Improvements in the speed of information transmission, c. 1820 1870. *European Review of Economic History* 5 (01), 1–28.
- Paddrick, M., Park, H., Wang, J. J., 2016. Bank networks and systemic risk: Evidence from the national banking acts. Tech. rep., Office of Financial Research, Washington, DC.
- Sprague, O. M. W., 1910. *History of Crises Under the National Banking System*. Washington, DC: Government Printing Office.