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ABSTRACT

We employ a unique hand-collected dataset and a novel methodology to examine systemic risk before and after the largest U.S. banking crisis of the 20th century. Our systemic risk measure captures both the credit risk of an individual bank as well as a bank's position in the network. We construct linkages between all U.S. commercial banks in 1929 and 1934 so that we can measure how predisposed the entire network was to risk, where risk was concentrated, and how the failure of more than 9,000 banks during the Great Depression altered risk in the network. We find that the pyramid structure of the commercial banking system (i.e., the network's topology) created more inherent fragility, but systemic risk was nevertheless fairly dispersed throughout banks in 1929, with the top 20 banks contributing roughly 18% of total systemic risk. The massive banking crisis that occurred between 1930–33 raised systemic risk per bank by 33% and increased the riskiness of the very largest banks in the system. We use Bayesian methods to demonstrate that when network measures, such as eigenvector centrality and a bank's systemic risk contribution, are combined with balance sheet data capturing ex ante bank default risk, they strongly predict bank survivorship in 1934.

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1 Introduction

The Global Financial Crisis (GFC) focused attention on the importance of understanding the connections between financial institutions, which have been seen as a means for propagating distress (Allen and Gale, 2000; Elliott et al., 2014; Acemoglu et al., 2015; Allen et al., 2010; Freixas et al., 2000; Dasgupta, 2004; Caballero and Simsek, 2013). Researchers and policymakers have sought a better understanding of the characteristics that predispose financial systems to systemic risk as well as the potential negative macroeconomic externalities when "systemically important" financial institutions suspend or fail.[1]

In response, researchers have developed new analytical measures aimed at quantifying institutional as well as aggregate risk.[2] These tools provide new insights into the interpretation of systemic risk, although researchers continue to explore their properties and utility for policy makers. To date, studies have largely focused on the period around the GFC. This is somewhat surprising, given the well-documented challenges of measuring connections between the "shadow banking system" and the regulated sector of the 2000s, a need to understand the "out of sample" properties of these tools, and the benefits from comparing the GFC to earlier crises.[3]

To shed further light on these issues, we analyze how the largest financial crisis of the 20th century – the Great Depression – altered the network of financial institutions in the United States. To do so, we construct network measures using a new data set of correspondent banking relationships for all commercial banks and trusts in the United States in 1929 and 1934. In contrast to most recent approaches that estimate financial linkages from financial flow data, our measure of connectedness for 1929 and 1934 uses stated bank correspondent relationships based on historical bank records.[4]

We then develop tools to compute individual bank risk and systemwide risk to measure the exposure of the entire commercial banking network to risk before the Great Depression began, and

[1]The Dodd Frank Act (2010) defines a systemically important financial institution (SIFI) as one that is large, complex, linked to other financial institutions and "critical," providing services that may have few close substitutes. For an example of a model linking systemic risk externalities to measurement of it, see Acharya et al. (2017).

[2]For a survey of methodologies, see Bisias et al. (2012).

[3]Research is now beginning to explore them in the context of earlier periods. For example, see Brownlees et al. (2017), which tests a variety of empirical measures of systemic risk on a small subset of commercial banks. By contrast, our research models the connections across an entire network and for a particular crisis.

[4]For example, Billio et al. (2012) construct networks of financial institutions using bivariate Granger causality regressions based on inferences from asset returns. Exceptions are Burdick et al. (2011); Brunetti et al. (2017), which examine the properties of "physical connectedness" for U.S and European banks, respectively, during the 2007-8 crisis.

analyze where and how much risk was concentrated in individual banks within the network. We assess whether the pyramid-like structure of the banking system that existed prior to the Great Depression concentrated risk, and how counterfactual failures or interventions to rescue systemically important banks would have changed overall systemic risk. We examine how the failure of nearly 9,000 banks between 1930–33 altered risk within the system. Finally, we test whether the 1929 network measures of connectedness and risk are useful in predicting subsequent failure. The pyramid topology, geographical distribution of risk, and various network positions of the thousands of bank failures make studying the Great Depression a useful contribution to the systemic risk literature. These features are unlike the recent crisis and are important for understanding the impact of crises on networked systems.

We find network features can quantify the predisposition of financial systems to risk. In particular, we show that, even within the class of "scale-free" networks, a particular topology can amplify risk. Relative to a "random graph" topology, the pyramid-like structure of the commercial banking system that existed in 1929 increased fragility and the propensity for risk to spread by concentrating banking interactions to particular nodes in the network. That said, systemic risk was fairly dispersed in 1929, with the top 20 banks contributing roughly 18% of total systemic risk.

Because our risk measure can be decomposed to show an individual bank's contribution to systemic risk, we assess if network features are helpful in predicting whether individual banks failed or merged during the severe banking crisis of the early 1930s. Using marginal likelihood computations, we show that when network measures such as eigenvector centrality and a bank's systemic risk contribution are combined with balance sheet data that capture ex ante bank default risk, they strongly predict bank survivorship in 1934. Banks more central to the system or with higher ex ante default risk were more likely to subsequently fail. On the other hand, we find that a bank's individual contribution to systemic risk positively impacts survivorship, an interesting result in light of the large-scale intervention by the Reconstruction Finance Corporation to rescue banks beginning in 1932 and perhaps the wellspring of American "too big to fail" banking policy. Bayesian model selection and in-sample hit rates dramatically favor a specification when network measures are included, suggesting network-based systemic risk measures may have considerable utility for policy makers wanting to understand where risk lies in the system and the implications of that risk.

Having identified where risk resided in 1929, we show that, of the 20 systemically riskiest banks prior to the Depression, only one of them subsequently failed, raising overall systemic risk per bank by 1.59%. This result is largely because the systemically riskiest banks, while central to the network, had below average credit risk going into the Depression. They flexed, in response to massive withdrawals of deposits, but for the most part, did not break. Had all 20 of them instead failed, systemic risk would have risen by over 50%. Bank failures in the early 1930s were largely concentrated in smaller– and medium–sized institutions, and the 30 largest realized bank suspensions of the Great Depression were not central to the correspondent network system, accounting for only 8.33% of aggregate systemic risk in 1929. We also find that the massive banking crisis of the early 1930s reshaped the network and redistributed risk: it raised systemic risk per bank by 33% and increased the riskiness of the 20 largest banks in the system by 5 percentage points. The distribution of risk thus became more concentrated at the top of the system.

2 Data

To construct network measures and to compute individual bank risk and systemwide risk, we use information on the correspondent relationships for all commercial banks and trusts in the United States in 1929 and 1934. Institutional linkages, as used here, report on observed network relationships rather than those inferred from data, although, like many other network measures for banks, the data cannot quantify the intensive margin (i.e., we lack information on the precise size of the balance sheet connections between financial institutions). Correspondent relationships initially arose to service the needs of customers conducting business in larger cities and the financial centers of the United States in the 19th century, and were later reinforced by banks that met mandated regulatory reserve requirements by maintaining balances in larger city banks.

We collected data on correspondent relationships for the entire banking system in 1929 (roughly 26,000 banks) and in 1934 so that we could analyze how the system changed as a result of the banking crisis of 1930-33.[5] These data, as well as information on each bank's balance sheet and other characteristics (location, population of city or town, date of first charter, Federal Reserve membership, etc.), were hand collected from Rand McNally *Bankers Directory* (July 1929, September 1934). On the liabilities side, the publication lists four items: paid-up capital, surplus and profits, deposits, and other liabilities. Rand McNally also records four categories on the asset side of the ledger: loans and discounts, bonds and securities, miscellaneous assets, and cash and exchanges

[5] Foreign correspondents exist for some large city banks in locations such as New York and San Francisco. These are excluded from our analysis.

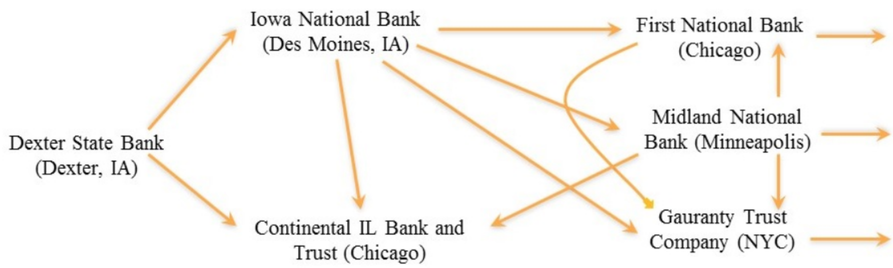

Figure 1: Illustrating correspondent relationships.

(due from banks). In describing directional relationships within the network, a "respondent" is defined as a bank that initiates a business relationship with another bank for its customers or itself (i.e., to satisfy reserve requirements by holding interbank deposits at a bank in a large city). A "correspondent" bank is the bank that satisfies those business needs. Because Rand McNally reports these precise correspondent relationships, we initially coded the relationships directionally, as illustrated in Figure 1. Dexter State Bank located in Dexter, Iowa, lists two banks as its correspondents in 1929: Iowa National Bank (Des Moines, IA) and Continental Illinois Bank and Trust (Chicago, IL). The correspondent bank Iowa National Bank in turn lists First National Bank (Chicago, IL), Continental Illinois Bank and Trust, Midland National Bank (Minneapolis, MN), and Guaranty Trust Company (New York) as its correspondents. Since we lack data on the intensive margin, we follow other analyses of financial networks and treat linkages equally in the data (i.e., no adjustments are made for differences in flow).

3 The 1929 Network

We begin by describing the contours of the network just prior to the Great Depression. In July 1929, 26,671 respondent banks and 4,204 unique correspondent banks existed. Our data set shows the complete list of relationships between these financial institutions. After removing rows and columns in which correspondent banks did not have a relationship with a respondent bank, we are left with 25,144 rows (respondents) and 3,602 columns (correspondents) for 1929. This matrix is "sparse" since many of the elements are zeros.

In 1929, there are $3,062$ banks that were both correspondents and respondents. Hence, the number of banks having at least one relationship with another bank is $25,684$ $(= 25,144 + 3,602 - 3,062)$; this determines the number of nodes n in the network graph. Correspondent banks that

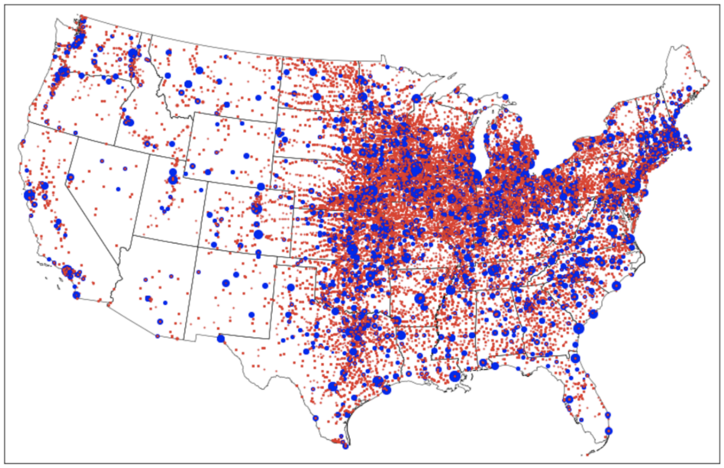

Figure 2: Respondent banks in red and correspondent banks in blue, sized by relative degree of each bank. Respondent banks place money with correspondent banks. Correspondent banks are plotted in blue and have points that are two times 1 plus the natural logarithm of the node's degree.

are not also listed as respondents are typically non-depository institutions and international banks, for which we do not have balance sheet data. Finally, the relationship between respondent and correspondent banks is a many-to-many relationship, meaning each respondent bank may be related to more than one correspondent bank, and vice versa.

The adjacency matrix for the network is defined as $A(i,j)$, $i,j = 1,2,...,n$, where $n = 25,684$ for 1929. $A(i,j) = 1$ if respondent bank i has a relationship with correspondent bank j, else $A(i,j) = 0$. The total number of links in the network is 70,679. Examining their distribution, most respondent banks have very few correspondents. On the other hand, correspondent networks can be very large – in the thousands – a fixture that has implications for the shape of the network. Figure 2 plots the locations of correspondent and respondent banks in 1929. If a bank is both a respondent and correspondent, it is plotted as a correspondent bank. The size of the point for correspondent banks is proportional to 1 plus the natural logarithm of the degree of the node and is plotted in blue color. Respondents are in red.

Correspondent banks are clearly more connected. Country banks, the term used to describe banks located in small towns and cities, are close to their correspondents, which explains the widespread geographical coverage by correspondent banks. Nevertheless, correspondent banks appear to be located in larger cities.

3.1 Network Statistics

To better understand the structure of the commercial bank network prior to the Depression, we compute a variety of common network statistics. We first examine the density of the network. Clusters, defined here as the number of disjoint connected components, describe one aspect of network connectivity. In 1929, there were 31 such disjoint groups. Of these, there is one extremely large connected component of 25,576 banks (out of a total of 25,684). Therefore, the banking network is almost fully connected. The remaining 30 components have sizes of 22, 12, 9, 6, and the rest have four nodes or less.

The number of links that a node has is known as its degree, and the computation of degree is directionless. That is, even though our network is directed, degree only depends on a node's links, regardless of the directional linkage (i.e., respondent to correspondent or correspondent to respondent). For 1929, the mean degree of nodes in the network is 5.50 with a standard deviation of 49.60.[6] The median degree in the network is 3.0 in 1929.

The "degree distribution" of the nodes is shown in Figure 3. The left plot shows nodes with degree less than 50 while the right plot shows nodes with degree greater than 50. The distribution is extremely skewed with a large number of nodes with low degree and a few nodes of very high degree.[7] We can also examine this feature by plotting the (log) number of nodes against the (log) number of links (degree). Figure 4 shows the expected quasi-linear and negative relationship characteristic of a log-log plot of a network, where we have excluded extreme nodes with degree greater than 50. The data on bank nodes exhibit the usual power law distribution that is characteristic of social networks (Barabasi, 2002; Barabasi and Bonabeau, 2003; Gabaix et al., 2003). The power law coefficient $\alpha = -1.65$.

Understanding which nodes have the greatest influence in the network, i.e., which nodes are the most critical, is also of interest, especially for policymakers who might want to identify "too big to fail" or systemically important institutions (SIFIs). Although there are many ways to capture this mathematically, we use several variants of the most common measure, centrality. First, centrality can simply be measured by the number of connections a node has, i.e., its degree; this is known as degree centrality. Of course, degree centrality ignores the fact that a node with few connections may

[6] Note that the number of links per node is the number of links divided by the number of nodes, i.e., $70679/25684 = 2.75$. Since each link connects two nodes, it accounts for two degrees. Therefore, the mean degree of the network is twice 2.75, i.e., 5.50.

[7] This is characteristic of a scale-free network. For a full exposition, see http://barabasi.com/f/623.pdf. See also Barabasi and Bonabeau (2003).

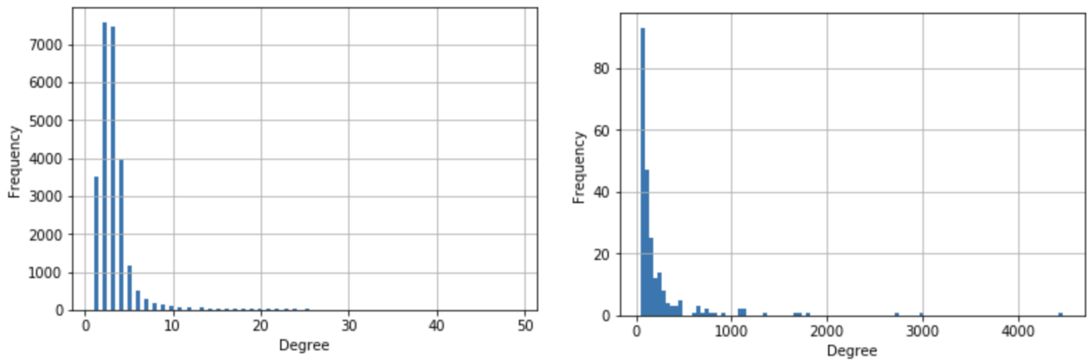

Figure 3: Degree distribution in 1929. The left panel plots nodes with degree less than 50 while the right panel plots nodes with degree greater than 50.

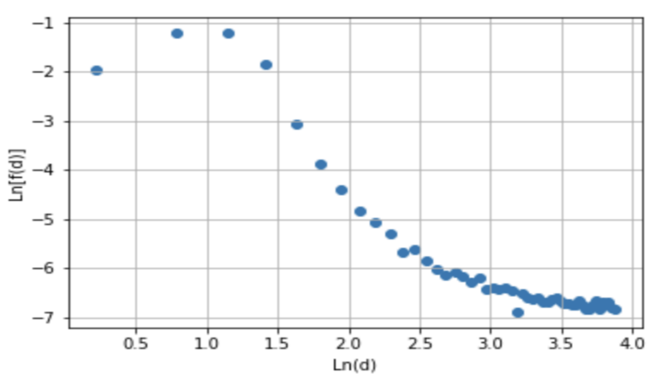

Figure 4: Log-log plot of the degree distribution in 1929 excluding extreme nodes with degree greater than 50. We plot log degree on the x-axis and log of the density function on the y-axis. For power-law densities, the function is $f(d) = d^{-\alpha}$. Taking logs we have $\ln[f(d)] = -\alpha \ln(d)$. The power law coefficient is $\alpha = -1.65$.

still have a huge influence if it is connected to a node with many connections.[8] Degree centrality may be varied by computing degree to a chosen depth, say three levels deep, a parameter chosen at the discretion of the modeler. The top banks by degree centrality in 1929 are shown in Table 1.

A more general formulation is eigenvalue centrality (Bonacich, 1987; Bonacich and Lloyd, 2001), where centrality (c_i) of a node is defined as a function of the centrality of the nodes to which it is connected, through the network matrix, A. This leads to a circular system of n simultaneous equations:

$$c_i = \sum_{j=1}^{n} A_{ij} c_j, \quad \forall i = 1, 2, ..., n. \tag{1}$$

This system of equations may be written in matrix form such that:

$$\lambda c = A \cdot c \tag{2}$$

where λ is a scalar quantity, c is a vector of size n, and as before, $A \in \mathcal{R}^{n \times n}$. Equation (2) is an eigensystem, and one solution to this system of equations is the principal eigenvector in an eigenvalue decomposition of adjacency matrix, A. This is known as the centrality vector, which contains n components, $c_i, i = 1, 2, ..., n$. Eigenvalue centrality is equivalent to degree centrality computed with infinite degree depth. The banks with the most eigenvalue centrality are also shown in Table 1.

As shown in Table 1, Continental Illinois Bank and Trust (Chicago) has the most linkages in the network, with 4,474 in 1929. Chase National Bank is second (in both degree centrality and eigenvalue centrality) with 2,982 linkages. Eight of the top 15 banks with the highest degree centrality are located in the financial centers of New York City and Chicago. In 1929, these were known as central reserve cities since non-Fed member banks could satisfy their state-mandated reserve reserve requirements by holding reserves in banks located in these cities. The other seven are in reserve cities of the Federal Reserve system. Combined, these locations give rise to the pyramid structure analyzed in the next section.

A third measure for determining the importance of nodes is betweenness centrality, which assigns importance to a node in a network if it sits at the intersection of paths between other nodes. In this context, a node has importance because it acts as an information "broker." Betweenness centrality is calculated as the number of shortest paths in the graph that pass through a given node. Following

[8]For example, in a social network, one may have very few friends, but if one of them is Mark Zuckerberg, then one still has a lot of influence.

Table 1: Top 15 banks by 1929 eigenvalue centrality (normalized), along with their degree.

Bank Name and Location	Centrality	Degree
Continental Illinois Bank and Trust (Chicago, IL)	1.000	4,474
Chase National Bank (New York City, NY)	0.440	2,982
Central Hanover Bank and Trust (New York City, NY)	0.283	2,710
First National Bank of Chicago (Chicago, IL)	0.279	1,715
National City Bank (New York City, NY)	0.265	1,778
Guaranty Trust Company (New York City, NY)	0.226	1,652
First National Bank in St. Louis (St. Louis, MO)	0.181	1,113
Philadelphia National Bank (Philadelphia, PA)	0.181	1,127
Mercantile Commerce Bank and Trust (St. Louis, MO)	0.148	813
Union Trust Company (Cleveland, OH)	0.146	629
First Wisconsin National Bank (Milwaukee, WI)	0.140	741
First National Bank (Minneapolis, MN	0.139	1,090
National Park Bank (New York City, NY)	0.125	1,370
First National Bank (St. Paul, MN)	0.123	736
Irving Trust Company (New York City, NY)	0.109	1,107

Table 2: Top ten banks by betweenness centrality (1929).

Bank Name and Location
First National Bank of Chicago (Chicago, IL)
Security First National Bank of Los Angeles (Los Angeles, CA)
Union Trust Company (Cleveland, OH)
American Trust Company (San Francisco, CA)
Citizens National Trust & Savings Bank (Los Angeles, CA)
Mississippi Valley Merchants State Trust Company (St. Louis, MO)
Mercantile Commerce Bank and Trust Company (St. Louis, MO)
Fifth Third Union Trust Company (Cincinnati, OH)
Mellon National Bank (Pittsburgh, PA)
The Philadelphia National Bank (Philadelphia, PA)

Freeman (1977), betweenness centrality for a node v is defined as follows:

$$b_v = \sum_{i,j} \frac{g(i,v,j)}{g(i,j)} \tag{3}$$

where $g(i,v,j)$ is the number of shortest paths from node i to node j that pass through node v, and $g(i,j)$ is the number of shortest paths from node i to node j. The summation is taken over all (i,j) where $i \neq j \neq v$ and $i \neq v$. Centrality is normalized, with the highest scoring (most important) bank being set equal to one and others set relative to this value.

Interestingly, the results differ when considering betweenness centrality. Only one of the top 10 banks using this measure are located in the central reserve cities of New York and Chicago (versus the majority of banks for the two other measures). As Table 2 shows, using betweenness centrality, the most influential connector nodes are coast-to-coast and geographically dispersed.

3.2 The Pyramid Structure of the 1929 Network

Financial historians provide us with some priors about the general topology of the network in 1929 – features that evolved out of the evolution of correspondent banking. Their descriptions point toward a network topology resembling a pyramid, where banks in cities, such as New York and Chicago, had the greatest number of connections; those in other large cities, such as St. Louis, Philadelphia, and San Francisco, had fewer linkages; and banks in small towns and cities had the least. In this section, we explore the extent to which their priors are confirmed by the data, and examine the degree to which the topology of the network predisposes the system to risk.

The structure of the correspondent banking network that existed on the eve of the Depression had evolved over the course of the nineteenth century, especially after the Civil War and the establishment of nationally chartered banks. As the nation grew and population moved westward, banks located in smaller towns and cities sought correspondent linkages with financial centers to carry out business on behalf of their customers as well as on their own account. Further, the National Banking Act of 1864 led to increased circulation of bank drafts as a national payments instrument (James and Weiman, 2010). It had the effect of solidifying the importance of New York correspondent banks at the apex of an emerging pyramid-shaped correspondent network as these centrally-located banks could mediate payments of bank drafts between parties regardless of their location (Redenius, 2007; James and Weiman, 2011). The national banking acts of the 1860s further required “country banks” (those located in the hinterlands) with national bank charters to meet legal reserve requirements by keeping a portion of their reserves as cash in their vaults and the remainder (originally up to three-fifths) in correspondent banks in "reserve" or "central reserve cities" (larger cities dispersed throughout the country). State laws (applying to those banks that received charters to operate from state banking authorities) reinforced the need for correspondent relationships by also requiring state-chartered banks to split their reserves between vault cash and interbank balances kept in the larger city banks.

Thus, as a result of the growth of a national payments system and regulations, interbank deposits were particularly concentrated in reserve and central reserve cities, and fostered a pyramid-like structure in terms of correspondent relationships.[9] The Federal Reserve Act altered the structure of reserves, with framers imagining a system whereby banking panics (not uncommon in the late 19th century) would be reduced by consolidating deposits in one of the Fed's 12 regional reserve banks instead of being scattered among hundreds of commercial banks in scores of reserve cities.[10] The Federal Reserve Act, as amended in 1917, required national and state-member banks to meet their reserve requirements entirely by holding deposits at their regional Federal Reserve Bank. By 1929, however, only 10% of state-chartered commercial banks had joined the Federal Reserve System.

Since roughly 90% had declined to join, much of the reserve pyramid remained in place in 1929 (Mitchener and Richardson, 2019). Non-member banks continued to meet their state-mandated reserve requirements by holding interbank deposits at banks in one of the 63 reserve cities as well as Chicago and New York – the central reserve cities. They also held their excess reserves in these reserve-city banks, which they used to manage liquidity and offer a broader array of services to their clientele.[11] To a large degree, then, this pyramid structure was a relic of the national banking era (when regulations allowing reserve requirements to be met by holding them in larger-city banks were first imposed (Anderson et al., 2018a), and the subsequent failure of the Federal Reserve System to convince all state-chartered banks to switch their charters and join the system after 1914

[9]This reserve pyramid proved ineffective during large financial crises of the nineteenth century, when reserves became difficult, and at times impossible, to access. When faced with widespread demands for cash and credit, reserve city banks hoarded funds for their own defense and left country banks to fend for themselves. As a result, banking panics periodically shut down the payments system (Kemmerer, 1922; Sprague, 1910). The pyramid structure was thus more effective at satisfying needs arising around the payments system than it was at providing liquidity to distressed institutions.

[10]For a detailed analysis of the interbank network and 19th century crises, see Calomiris and Carlson (2017). For additional research on how the founding of the Federal Reserve influenced the interbank market, see Carlson and Wheelock (2016) and Carlson and Wheelock (2018).

[11]Federal Reserve member banks also deposited excess reserves at correspondent banks in reserve and central reserve cities, since commercial correspondent accounts paid a higher interest rate (typically 2%) than Federal Reserve Banks (typically 0%). This was particularly true of reserve-city banks, which deposited their excess reserves in money-center banks in New York and Chicago. In June 1929, member banks held 93% of all interbank deposits in the United States. Nonmember banks held only 7%.

(Anderson et al., 2018b).

To examine the properties of this particular network topology, and in particular how they relate to systemic risk, we compare the diameter and fragility of our network to a random graph network. Diameter is defined as the maximal shortest path between any pair of nodes in the cluster for a non-directional network. It is the max-min measure over all paths between all pairs of nodes. This is a measure of how many banks it takes for a financial flow to spread from one edge of the network to the other, thus giving us some insight into how quickly "contagion" could occur. The bigger the diameter, the less likely that a local financial shock will become a global event in a banking system. We define the concept of "system fragility" as the Herfindahl index normalized by dividing by mean degree: $R = E(d^2)/E(d)$, where d is degree of each node. Fragility takes concentration more explicitly into consideration than diameter because a highly-concentrated network tends to have a greater risk of transmission. If a highly central node is compromised, the propensity for risk to spread to the other nodes is high, which is captured by fragility.

We begin with an example that illustrates the differences between a pyramid structure and a random graph. Pyramid graphs are mostly tree-like, even though they are not directed acyclic graphs (or DAGs). Panel A of Figure 5 displays an undirected graph of 10 nodes, where a principal node 1 is connected to nodes 2, 3, and 4. Node 2 is then connected to nodes 1, 5 and 6, node 3 is connected to 1, 6, 7, 8, and node 4 is connected to 1, 9, 10. This looks like a tree but the specification of node 1 at the top of the tree is artificially imposed – one can just as easily "pick up" any other node and make it the root of the tree (or the apex of the pyramid). Topologically, pyramid graphs are likely to have degree (connections) concentrated in a few nodes, and are within the class of scale-free networks (Barabasi and Bonabeau, 2003; Barabasi, 2002). The graph in Figure 5 (Panel A) has mean degree of 2.2 connections per node. For comparison, we also generate a random graph of 10 nodes with mean degree 2.2 (Panel B of Figure 5). Even though both graphs have the same mean number of connections per node, the concentration of connections in a few nodes is higher in the former. A measure of node importance is "centrality," analytically described earlier. The normalized mean centrality for the pyramid network is 0.65 versus 0.60 for the random network.

The diameter of the pyramid network as well as the random network is 4, whereas fragility is equal to 2.91 for the pyramid and 2.64 for the random network. These results suggest that, all else equal, contagion will spread faster in the pyramid network because its connections are more

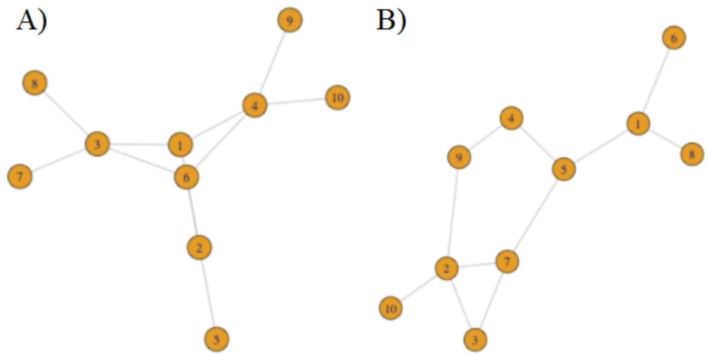

Figure 5: Panel A is a depiction of a pyramid graph with 10 nodes. Note that the graph when laid out does not necessarily look like a tree. The mean degree is 2.2. Panel B is a depiction of a random graph with 10 nodes and mean degree 2.2. Repeated simulations confirm the stability of this result.

concentrated.

Having considered how topology matters for risk, we now turn to examining the actual network for 1929. The 1929 network contained 25,684 nodes and mean degree of 5.5. For comparison, we generated a random network with the same number of nodes and mean degree.[12] The pyramid network has a diameter of 13 (average shortest path length was 3.31) and fragility of 453, whereas the random network has a diameter of 12 and a fragility of 6.5. The pyramid structure in existence prior to the banking distress of the Great Depression made the network inherently more fragile than a random network by increasing the centrality of particular nodes and concentrating risk.

4 Systemic Risk

4.1 Risk Scoring

We now turn to measuring systemic risk. We develop measures of both individual bank credit risk as well as aggregate system-wide risk that incorporate the interconnectedness of banks noted in the previous section. In order to construct the systemic risk score, we needed to quantify the credit quality of all commercial banks. Since credit ratings were non-existent for the tens of thousands of banks that were too small to be listed on the NYSE, we employ financial ratios to develop a composite measure of credit risk, a product of inverse profitability and transformed leverage. We combine this with the network matrix to create a *systemic risk per bank*.

We begin with bank-level balance sheet and income data to derive bank-specific measures of

[12]We generated several random networks and the results align with the presented case.

risk and define and/or compute the following financial ratios:

1. Assets – the sum of loans and discounts, miscellaneous assets, bonds and securities, and cash and exchanges;

2. Equity – the sum of paid-up capital plus surplus and profits;

3. Leverage – assets divided by equity;

4. Buffer stock of retained earnings (BUF) – stock of retained earnings (surplus and profits divided by equity).[13]

We convert profitability into a risk score (C) using the following function of BUF, i.e., an inverse profitability risk score:

$$C = a + \frac{1}{1 + BUF} \cdot b \tag{4}$$

where $a = -8$ and $b = 18$. We can see that $C \in (1, 10)$ because $BUF \in (0, 1)$. An increasing score implies greater risk. The mean credit risk score is 5.02 (median 4.90), with a standard deviation of 1.92. The minimum and maximum scores are 1 and 10. The largest ten banks ranked in terms of equity are shown in Table 3 alongside their credit risk scores and leverage ratios. Interestingly, all of the largest banks have risk scores below the mean in 1929. Additionally, the most connected banks in Table 1 have below average credit risk scores. Much of the balance sheet risk in the system resided in medium to smaller sized banks.

We also transformed our leverage ratio in Table 3 to deal with an artificial right skew arising from positive outliers in the data, i.e., banks with very low equity. Leverage-based risk (L) is thus calculated as the following transformed value:

$$L = \ln(1 + Assets/Equity). \tag{5}$$

Leverage-based risk has a mean of 2.10 and a standard deviation of 0.38.

Finally, we compute a composite risk score, R, which combines the inverse of profitability measure, C, and transformed leverage, L, such that:

$$R = C \times L. \tag{6}$$

[13]This is close to a bank's return on equity, however, because we do not observe dividends paid out, it is not identical to it. It was nevertheless used by banks to expand operations or write off losses relative to the book value of net worth. See Carlson and Rose (2015).

Table 3: Credit Risk and Leverage for the 10 largest banks (as measured by equity).

Bank	Credit Risk	Leverage
National City Bank (New York City, NY)	3.750	8.783
Guaranty Trust Company (New York City, NY)	3.086	8.366
Chase National Bank (New York City, NY)	3.443	7.811
Continental Illinois Bank and Trust (Chicago, IL)	4.242	7.660
Irving Trust company (New York City, NY)	3.115	5.655
Bank of Italy Nat. Tr. & Sav. Assn. (San Francisco, CA)	3.769	8.016
First National Bank (New York City, NY)	1.447	5.208
Bankers Trust Co. (New York City, NY)	2.221	6.686
Central Hanover Bank & Trust Co. (New York City, NY)	2.054	6.031
Manufacturers Trust Co. (New York City, NY)	2.757	5.851

In the ensuing analysis of systemic risk, we focus on R since this metric has appealing properties. For example, because it is possible for firms with a high BUF to have low equity (and consequently high leverage), these firms would be quite risky, yet the measure C would not assign them as such. Multiplying C by L compensates for this possibility. R has a mean value of 10.52 and a standard deviation of 4.27.

The risk measure, R, is analogous to modern credit-scoring methods such as the probability of default which, for example, is computed using the Merton (1974) model. This model defines the distance to default (an input to computing probability of default) as a leverage-adjusted measure of volatility, providing the connection to our risk model here, where R is a leverage-adjusted measure of inverse profitability. We use R since there are no measures of asset volatility available for all banks in 1929.

4.2 Systemic Risk

We combine the network adjacency matrix A (described above) with the composite risk score for each bank in the vector R to create a single measure of systemic risk per bank. We extend and modify the metrics proposed in Das (2016) and Das et al. (2019). Our approach allows one to empirically estimate "exposure" despite not knowing everything we might want about the financial financial network. (For example, data on balance-sheet linkages between financial institutions is often opaque or incomplete, both historically and today.) Systemic risk per bank, S, is thus defined as:

$$S = \frac{1}{n} \cdot \sqrt{R^\top \cdot A \cdot R} \tag{7}$$

$$= \sqrt{\frac{R}{n}^{\top} \cdot A \cdot \frac{R}{n}} \quad (8)$$

$$= \sqrt{Q^{\top} \cdot A \cdot Q} \quad (9)$$

where n, as noted before, is the number of banks in the system, and superscript $\top$ denotes the transpose of a vector or matrix. (Recall that R is an n-vector and A is a $n \times n$ matrix. Thus, Q is an n-vector.) Division by n is a normalization used to measure systemic risk per financial institution and to account for the fact that the banking crises of the early 1930s drastically reduced the number of financial institutions in the network by 1934 – the year we use for post-crisis network comparison later in the paper. Equation (8) implies that systemic risk, as denoted by scalar quantity S, increases if the elements of R (individual bank risk) increase, holding n and A constant. Likewise, ceteris paribus, if the elements of A (interconnectedness of banks) increase, systemic risk per bank also increases. Note also that since the elements of R and A are all non-negative, S is also non-negative.

The systemic risk measure, S, may be thought of as a network, modified measure of composite credit risk in the banking system. We note that it can be decomposed into two components: (1) the amount emanating from individual bank risk and (2) that from network effects. If we replace the network matrix, A, with the identity matrix and recompute S, i.e., $S' = \sqrt{\sum_{i=1}^{n} R_i^2}$ then this measures composite emanating risk from individual bank risk only. The ratio $S/S' \geq 1$ is a measure of systemic risk arising from network effects.

Plugging the values from the 1929 data into these equations, we find that the total systemic risk per bank, S, is 0.104. The ratio $S/S' = 1.46$, suggesting that the network effect amplifies systemic risk by a factor of 1.46. By itself, the value carries little meaning, but since it can computed at different points in time (e.g. 1929 and 1934), the metric will allow us to examine how overall risk in the system changes as a result of the banking crises of the Great Depression. To understand where risk was concentrated prior to the Depression, we begin by breaking down systemic risk into the risk contribution of each bank in 1929. This decomposition of the scalar function $S(R, A)$ is possible because the function is linear homogeneous in vector $Q = [Q_1, Q_2, ..., Q_n]^{\top}$, the normalized value of R. We can apply Euler's homogenous function theorem and obtain the *risk decomposition equation*:

$$S = \frac{\partial S}{\partial Q_1} \cdot Q1 + \frac{\partial S}{\partial Q_2} \cdot Q2 + \ldots + \frac{\partial S}{\partial Q_n} \cdot Q_n. \quad (10)$$

Each partial derivative $S_j = \frac{\partial S}{\partial Q_j}$ multiplied by Q_j is the risk contribution of bank j. We can

Table 4: Top 20 banks by percentage contribution to systemic risk, 1929.

Bank Name and Location	Percentage Risk
Continental Illinois Bank and Trust (Chicago, IL)	3.228
Chase National Bank (New York City NY)	1.557
The National Bank of the Republic of Chicago (Chicago, IL)	1.206
First National Bank of Chicago (Chicago, IL)	1.191
Commerce Trust Company (Kansas City, MO)	1.054
National City Bank (New York City, NY)	1.043
First National Bank (Minneapolis, MN)	0.969
First National Bank in St. Louis (St. Louis, MO)	0.845
Central Hanover Bank & Trust Company (New York City, NY)	0.762
Guaranty Trust Company (New York City, NY)	0.744
First National Bank of St. Paul (St. Paul, MN)	0.627
First Wisconsin National Bank (Milwaukee, WI)	0.619
National Stock Yards National Bank (National Stock Yards, IL)	0.606
National Park Bank (New York City, NY)	0.600
Mercantile Commerce Bank & Trust Company (St. Louis, MO)	0.594
Fletcher American National Bank (Indianapolis, IN)	0.457
Northwestern National Bank (Minneapolis, MN)	0.452
Union Trust Company (Cleveland, OH)	0.451
Fidelity National Bank and Trust Company (Kansas City, MO)	0.419
Drovers National Bank (Chicago, IL)	0.414

calculate all derivatives S_j in closed form using the following vector derivative:

$$\frac{\partial S}{\partial Q} = \frac{1}{2S}[A \cdot Q + A^{\top} \cdot Q] \in \mathcal{R}^n \tag{11}$$

which gives an n-vector of derivatives S_j. Once we know the amount of risk that is contributed by each node, we can pinpoint the riskiest banks in the network in terms of their contribution to overall systemic risk.

Computing this for the 1929 data, we calculate each bank's contribution to S. Table 4 shows the percentage of systemic risk contributed by each of the top 20 risk contributing banks. Comparing it to Table 1, we can see there is a considerable correspondence between the banks exhibiting the most systemic risk prior to the Great Depression and the banks showing the greatest centrality. However, an important additional feature of the 1929 network is that systemic risk is dispersed across the entire network. Taken together, the top 10 banks account for 12.6% of the total systemic risk and the top 20 banks account for 17.8%.

We also recomputed the risk score in equation (6) using size weights based on bank assets, i.e., we redefined $R = C \times L \times w$, where w is an asset-based weight, such that if the bank was in the top

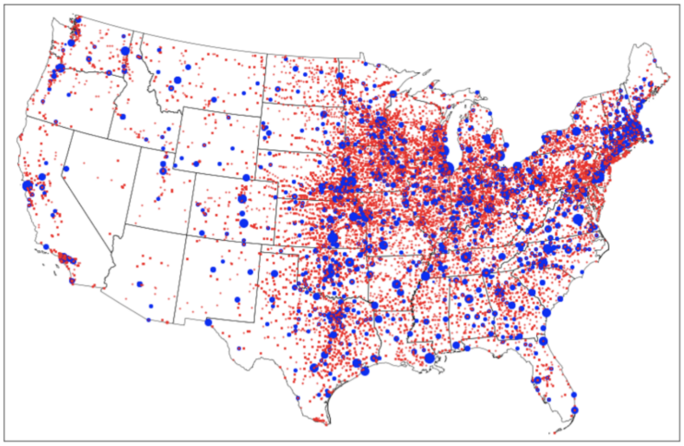

Figure 6: Respondents and Correspondents, 1934.

size decile by assets, then $w = 3$, and if it was between the 40th and 90th percentile, it was given a weight of $w = 2$. All banks below the 40th size percentile had weight $w = 1$. We recomputed the results in Table 4 and noticed no material changes. Therefore, the systemic risk measure is robust to size-weighting of individual bank risk.

5 The Impact of the Financial Crisis on the Network

5.1 Network Features

As has been well documented by economic historians, waves of banks failures between 1930–1933 irrevocably altered the US financial system.[14] Distress occurred throughout the country, but especially in rural areas and smaller towns. Using the 1934 data, we explore how the more than 9,000 banks that exited the system altered the structure of the network. Between 1929 and 1934, the number of respondent banks declined by 36% (from 25,144 to 16,126) while the number of correspondents fell by 41% (from 3,602 to 2,134). The number of banks in the network declined by 36%, from 25,684 in 1929 to 16,446 in 1934, and the total number of links in the network fell by 41%, from 70,583 in 1929 to 41,313. Comparing Figures 2 and 6 illustrates these changes spatially, showing a substantial amount of thinning in both red and blue dots.

The number of clusters (disjoint groups) fell from 31 to 27, but the system still retained one large connected component with 16,380 nodes out of a total of 16,446. The mean degree of nodes in the network declined slightly between 1929–1934, from 5.50 to 5.02. Other than the median degree

[14] For example, see Friedman and Schwartz (1963) and Wicker (1996).

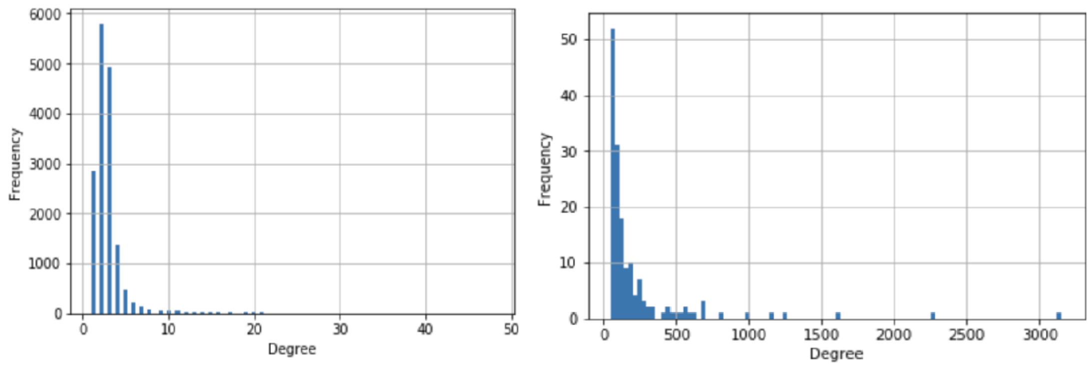

Figure 7: Degree distribution for the banking network in 1934. The left plot shows the distribution for nodes of size 1-50, and the right plot shows the distribution for nodes of size greater than 50.

in the network falling from 3 in 1929 to 2 in 1934 (reflecting the disappearance of many smaller banks from the system), the frequency plots of the degree of nodes for 1929 and 1934 look quite similar: the 1934 system still exhibits the usual power law distribution (power coefficient $\alpha = 1.60$) with the bulk of mass at low nodes and just a few banks having extremely large numbers of nodes (Figure 7).

Table 5 displays the most central banks in 1934. Because Chicago experienced two pronounced banking panics in 1931–32, Continental Illinois lost several thousand of its respondents to failure (Friedman and Schwartz, 1963; Calomiris and Mason, 1997), and thus slipped from being the bank with the highest degree centrality in 1929 to second overall in 1934. Chase National Bank gained a few hundred connections. Table 6 shows that for betweenness centrality, the top banks change considerably in comparison to 1929, with only four from that year remaining in the top 10 (with new entrants shown in italics in Table 6). The greater degree of temporal change in betweenness centrality, relative to the other measures, likely reflects the fact that the banking crisis knew no geographical limits. That is, even in 1929, many of the most influential banks were located outside of the central reserve cities.

We can also compare how the diameter and fragility of the network changed over time. As a point of reference, we discuss these two measures in relation to those for the recent GFC. Between 1929 and 1934, the diameter remained the same at 13. The average shortest path length in 1934 was 3.25, similar to the 3.31 of 1929. Between 2005 and 2009, diameter remained quite stable, decreasing from 5 to 4 as the network shrank because of bank exits (see Burdick et al. (2011)). Therefore, the network was much wider in 1929 and 1934 compared to the recent financial crisis in the US.

Table 5: Top ten banks by eigenvalue centrality (1934), along with their degree. Centrality scores are normalized.

Bank and Location	Centrality	Degree
Chase National Bank (New York City, NY)	1.000	3,154
Continental Illinois Bank and Trust (Chicago, IL)	0.630	2,275
First National Bank of Chicago (Chicago, IL)	0.367	1,230
National City Bank (New York City, NY)	0.258	1,140
Philadelphia National Bank (Philadelphia, PA)	0.247	890
Central Hanover Bank and Trust (New York City, NY)	0.245	1,618
Guaranty Trust Company (New York City, NY)	0.237	1,004
First National Bank in St. Louis (St. Louis, MO)	0.230	683
Mellon National Bank (Pittsburgh, PA)	0.191	582
Commerce Trust Company (Kansas City, MO)	0.161	691

Table 6: Top 10 Banks in Betweenness Centrality, 1934. Banks in the top 10 in 1934 and not in 1929 are shown in italics.

Bank Name
First National Bank of Chicago (Chicago, IL)
Security First National Bank (Los Angeles, CA)
First National Bank in St. Louis (St. Louis, MO)
The Pennsylvania Company (Philadelphia, PA)
Republic National Bank and Trust (Dallas, TX)
Mellon National Bank (Pittsburgh, PA)
Mercantile Commerce Bank and Trust Company (St. Louis, MO)
The Boatmen's National Bank (St. Louis, MO)
Harris Trust and Savings Bank (Chicago, IL)
City National Bank and Trust Company (Chicago, IL)

Table 7: Credit Risk Scores and Leverage for the 10 largest banks (as measured by equity) in 1934.

Bank	Credit Risk	Leverage
Guaranty Trust Company (New York City, NY)	3.124	5.354
Chase National Bank (New York City, NY)	5.225	7.717
National City Bank (New York City, NY)	6.167	8.354
Irving Trust Company (New York City, NY)	3.468	5.141
Bankers Trust Company (New York City, NY)	2.432	8.496
Continental Illinois Bank and Trust (Chicago, IL)	7.285	8.086
First National Bank (New York City, NY)	1.457	5.068
Bank of America Nat. Tr. & Sav. Assn. (San Francisco, CA)	3.994	10.207
Central Hanover Bank and Trust (New York City, NY)	2.445	8.282
Manufacturers Trust Company (New York City, NY)	5.158	6.147

In 1934, fragility fell by roughly one-fifth, from 453 to 354, suggesting that the system displayed much more concentrated risk before the banking distress of the early 1930s. These numbers are much higher than in 2005 when fragility was 138 (see Burdick et al. (2011)). Fragility in 2006 rose to 172 and then dropped to 35 by 2009. While this was still high, system fragility during the GFC was smaller by orders of magnitude than in the Great Depression. This difference may be driven by the fact that analyses on 2005-2009 are performed on a small number of financial institutions.[15]

Table 7 displays how our risk measures changed as a result of the crisis. The mean credit risk score rose from 5.02 in 1929 to 5.65 (with an SD of 2.05) in 1934. Whereas all of the largest banks had risk scores below the mean in 1929, circumstances had changed this by 1934: both National City Bank of New York (6.17) and Continental Illinois (7.28) exceeded the mean of 5.65. Leverage-based risk (L) shrunk slightly from 2.11 in 1929 to 1.93 in 1934 (with an SD of 0.39). Using the composite risk score $R = C \cdot L$, we can see that by 1934, the banking crises had raised the average riskiness of banks, from a mean of 10.54 in 1929 to 10.76 (with as SD of 4.29).

Because overall connectivity decreased between 1929 and 1934 (with the mean degree falling) and balance-sheet risk, R, increased, the change in systemic risk S is not immediately clear. Using the A matrix and R vector from the 1934 data, we recompute S. In comparison to 1929 (0.104), total systemic risk per bank rose to 0.138. We thus find that the financial panics of the early 1930s increased systemic risk per bank by 33% – a dramatic change in a span of only 4.5 years.

[15] Comparing the Great Depression with the GFC is not precise by any means. The construction of networks in both periods uses quite different variables and there are differences also in the measure of bank credit quality, as different credit risk variables were developed and employed in modern times. Therefore, these comparisons should not be taken literally, but more as indicative of how financial crises change the structure of the banking system.

Table 8: Top 20 Systemically Riskiest Banks in 1934.

Bank Name	Percentage Risk
Continental Illinois Bank and Trust, (Chicago, IL)	4.21
Chase National Bank (New York City, NY)	3.68
First National Bank of Chicago (Chicago, IL)	2.16
National City Bank (New York City, NY)	1.60
Commerce Trust Company (Kansas City, MO)	1.22
First National Bank in St. Louis (St. Louis, MO)	1.06
Northwestern National Bank and Trust (Minneapolis, MN)	0.97
Central Hanover Bank & Trust Company (New York City, NY)	0.91
First National Bank and Trust Co. (Minneapolis, MN)	0.76
First Wisconsin National Bank (Milwaukee, WI)	0.74
Mercantile Commerce Bank & Trust Company (St. Louis, MO)	0.71
Omaha National Bank (Omaha, NE)	0.63
National Stock Yards National Bank (National Stock Yards, IL)	0.63
Guaranty Trust Company (New York City, NY)	0.55
First National Bank of St. Paul (Minneapolis, MN)	0.51
Fifth Third Union Trust Co. (Cincinnati, OH)	0.51
Philadelphia National Bank (Philadelphia, PA)	0.49
City National Bank and Trust Co. (Chicago, IL)	0.49
First National Bank (Kansas City, MO)	0.46
First National Bank (Boston, MA)	0.45

Given connectivity and balance sheet risk are moving in opposite directions, this number shows that increased balance sheet risk more than offset the decline in connectivity. Note, however, that the measure S/S', the network multiplier, is marginally higher at 1.53 than in 1929 (=1.46).

To investigate how the banking distress of the early 1930s redistributed risk, we can decompose our systemic risk measure and examine it bank-by-bank. Table 8 shows the percentage of systemic risk contributed by the 20 systemically riskiest banks in 1934. Comparing these figures to those from 1929 (Table 4) reveals that the banking crises of the early 1930s caused the concentration of risk in the network to rise. In 1934, the 10 systemically riskiest banks contributed 17% to overall risk (versus 13% in 1929), while the top 20 contribute to 23% of the overall systemic risk (versus 18% in 1929). Additionally, while Continental Illinois lost thousands of connections, its balance sheet risk increased enough so that it remains the systemically riskiest bank. These findings are important from a modern regulator's perspective because the network topology and number of failures are unlike the GFC and thus provide additional perspective on understanding systemic risk.

5.2 Counterfactuals and Realized Suspensions

An important question from a regulator's perspective is how overall systemic risk changes if something happens to one of the systemically riskiest banks? In this section, we discuss methods for considering counterfactuals and present the changes to systemic risk due to the largest realized suspensions that occurred during the Great Depression.

Our model allows us to consider the effects of two types of counterfactuals that affect systemic risk: (1) when banks are removed from the system (perhaps through supervisory action) and (2) when banks fail. We begin by noting that the risk contributions, such as those shown in Table 4, have a useful mathematical property. They approximate the percentage reduction in per bank systemic risk that occurs when any bank exits the system for some reason other than failure, e.g., ownership decides to voluntarily liquidate; it is correctly quantified by the risk contribution of the bank. For example, if Continental Illinois Bank and Trust, the top risk contributor in 1929, were to exit the banking network, then the per bank systemic risk metric, S, would decline by approximately 3.2%. Therefore, when a bank exits, system-wide risk falls by approximately the same amount that the bank contribute to overall systemic risk.

Given this insight, it follows that our analytic solution also permits direct measurement of the percentage reduction in systemic risk achieved if a bank were "quarantined." In this counterfactual, a bank is quarantined if it remains in the network, but is not allowed to fail. Such a situation could arise if a regulatory authority chooses to intervene during a crisis, perhaps if a bank is viewed as systemically important or "too big to fail." We can simulate this by setting the risk score, R, for the bank equal to zero (i.e., the government backstop), leaving it in the network, and then recalculating S. It turns out that this has the same effect as removing the bank from the network altogether. Therefore, if Continental Illinois were quarantined, risk falls by 3.2%. Even when a collection of banks is quarantined, the same result is realized. For example, if we allow the 10 riskiest banks in 1929 to be quarantined, the reduction in systemic risk is 13.5% and the sum total of their individual risk contributions is 12.7%.

The second counterfactual of interest considers how the hypothetical failure of an ex ante systemically important bank affects overall systemic risk. In our model, when a bank fails, risk in the system rises through its relationship to other banks in the adjacency matrix. We can simulate the failure of the of the 10 systemically riskiest banks by setting their risk score, R, equal to the maximum risk score across all banks in 1929. Table 9 displays the results of this simulation.

Table 9: The percentage increase in systemic risk if any one of the top 10 banks by percentage contribution to systemic risk fails.

Bank Name and Location	% Change S
Continental Illinois Bank and Trust (Chicago, IL)	12.939
Chase National Bank (New York City, NY)	8.139
The National Bank of the Republic of Chicago (Chicago, IL)	1.967
First National Bank of Chicago (Chicago, IL)	5.120
Commerce Trust Company (Kansas City, MO)	2.452
National City Bank (New York City, NY)	4.729
First National Bank (Minneapolis, MN)	3.742
First National Bank in St. Louis (St. Louis, MO)	3.105
Central Hanover Bank and Trust (New York City, NY)	8.093
Guaranty Trust Company (New York City, NY)	4.360

Clearly, systemic risk changes drastically if the riskiest bank, Continental Illinois Bank and Trust, fails: overall systemic risk S increases by approximately 13%. Chase National's bankruptcy would lead to over an 8% increase in S. The simultaneous failure of all 10 of the top contributors would raise systemic risk by over 50%, even without considering dynamic risk to the network (how it changes other banks' risks in the A matrix).

We now turn to the results for realized distress. In general, banks identified as the systemically riskiest prior to the start of the banking crises of the 1930s did not fail. Only one of the top 20 banks identified as the systemically riskiest in 1929 (Table 4), Union Trust Company (Cleveland, OH), failed, increasing systemic risk by 1.59%. Four others experienced suspended payments and subsequently experienced "distressed" mergers: National Park Bank (NYC), The National Bank of the Republic of Chicago, Fidelity National Bank and Trust Company (Kansas City), and Fletcher American National Bank (Indianapolis). The survival of most of the 20 ex ante systemically riskiest banks was buttressed by the fact that, on average, these banks had lower than average composite risk, R, in 1929. While they were central to the network, and thus "systemically important," their better financial position prior to the crisis allowed them to bend, but not break. Additionally, there was a large-scale bank rescue program that was implemented after the banking crises of the Great Depression had begun to ravage the country's financial system. The Reconstruction Finance Corporation (RFC) was established in early 1932. It initially offered collateralized loans to banks in need of assistance and later was given the authority to recapitalize them through preferred stock purchases. An interesting point is that about 70% of the 1929 top risk contributors received a large capital injection from the RFC. This suggests that regulators, even then, implicitly understood the

Table 10: Top 10 banks (by total assets) that suspended after 1929 and their contribution to systemic risk.

Bank Names	Loans (1000s)	% Change in S
Union Trust Company (Cleveland, OH)	189,563	1.586
The Bank of United States (NY)	213,403	0.028
First National Bank in Detroit (MI)	379,788	0.938
Guardian Trust Company (Cleveland, OH)	122,038	0.259
Guardian National Bank of Commerce (Detroit, MI)	109,856	0.438
Baltimore Trust Company (Baltimore, MD)	57,832	0.112
Ohio Savings Bank & Trust Co. (Toledo, OH)	44,261	0.155
The Bank of Pittsburgh N. A. (Pittsburgh, PA)	58,426	0.667
Hibernia Bank & Trust Co. (New Orleans, LA)	47,535	0.477
National Bank of Kentucky (Louisville, KY)	37,721	0.651

nature of risk in networked financial systems.[16]

Thus far, we have highlighted the risk contributions of the systemically riskiest banks before and after the crisis. However, our empirical design also allows us to examine how actual commercial bank suspensions occurring during the period of the banking panics (1930-33) altered systemic risk. We focus on the 30 largest realized suspensions, as measured by total loans and investments.[17] These include some of the most notorious banks failures during the Depression, such as the Bank of the United States, First National Bank of Detroit, Guardian National Bank of Commerce, and the two largest banks from the Caldwell chain of banks (National Bank of Kentucky and Central Bank and Trust Company).[18] These 30 suspensions accounted for a total of \$1.8 billion or 25% of the nation's loans and investments in suspended commercial banks.[19] The top 10 suspensions by total assets and their contribution to systemic risk are shown in Table 10. Although the Great Depression wiped out an inordinate number of banks, systemic risk arising from the realized suspensions of the 30 largest banks increased by 8.33% – considerably less than if the ex ante systemically riskiest bank in 1929, Continental Illinois, had failed (a resulting 13% increase).

6 Network Features and Bank Survivorship

[16]RFC assistance is not the same as the bank being "quarantined." Even Union Trust Company (Cleveland) failed despite receiving RFC assistance.

[17]Board of Governors (1936) (Table 18, p.36) provides data on the largest bank suspensions between 1929-33.

[18]See Heitfield et al. (2017) for an analysis of the banks that did business with Caldwell and Company.

[19]The mean size of bank failures for 1930-33 falls from \$954,000 to \$714,000 if these 30 banks are excluded. (Board of Governors (1936), p.34).

6.1 Predicting Bank Survivorship for the Entire Network

Because our underlying analysis is based on firm-level data, we can also analyze whether systemic risk measures improve prediction of subsequent banking distress – something that has been lacking in the literature on systemic risk. In this section, we use the sample of all banks operating in 1929 to predict bank survivorship in 1934. The outcome variable, y_i, thus equals 1 if bank i survives and appears in 1934 and equals 0 otherwise (i.e., we coded 0 as a bank failure).[20] 62% of the sample survives and the remainder exits.[21]

We consider two latent-variable models:

$$M_1: \quad y_i^* = x_{i1}^\top \cdot \beta_1 + \varepsilon_i \tag{12}$$

and

$$M_2: \quad y_i^* = x_{i1}^\top \cdot \beta_1 + x_{i2}^\top \cdot \beta_2 + \varepsilon_i. \tag{13}$$

For both, the mapping from the latent to the observed data is $y_i = 1\{y_i^* > 0\}$ and $\varepsilon_i \sim N(0,1)$, i.e., a probit model. The covariates in the vector x_{i1} include standard balance sheet measures, Federal Reserve membership, location information, and county characteristics for bank i in 1929.[22] The covariates in the vector x_{i2} include systemic risk measures for bank i in 1929, namely, composite risk score (R), eigenvalue centrality, and percent contribution to systemic risk. The specifications are purposefully parsimonious to offer simple interpretations and to help us examine the predictive power of our network measures. Other variables may also be important for modeling the causes of bank failures, but since our primary goal is to shed light on the *predictive* properties of network features, our benchmark model relies on bank specific characteristics, institutional features of the Federal Reserve system, and location controls.

The models are estimated by both maximum likelihood and Bayesian Markov chain Monte Carlo (MCMC) methods. The estimation results are similar across both methods; however, the Bayesian results permit us to compute marginal likelihoods and posterior model probabilities. Although the parameter estimates are interesting, again, our focus is on the predictive fit of our new measure - whether network features provide improved prediction. Thus, a fully Bayesian

[20] Banks are matched between 1929 and 1934 based on their name and routing number. Routing numbers are a useful matching tool for banks that have gone through name changes or charter changes.

[21] In this section, we do not differentiate between failures and mergers; however, in the following subsection, we disentangle failures and mergers.

[22] County information includes county population, manufacturing establishments, and acres of cropland. The data were collected from the 1930 *U.S. Census of Population, Manufacturing, and Agriculture.*

Table 11: Posterior means and standard deviations (in parenthesis) are presented for M_1 and M_2.

	M_1	M_2
Intercept	-1.469 (0.166)	-0.347 (0.177)
Loans/Deposits	-0.001 (0.003)	-0.004 (0.003)
Bonds/Assets	1.068 (0.052)	1.032 (0.054)
ln(Assets)	0.222 (0.008)	0.188 (0.009)
Eigenvalue Centrality		-5.887 (1.292)
Composite Risk Score		-0.061 (0.002)
SysRisk Percentage		2.196 (0.417)
Fed Member	0.051 (0.018)	0.060 (0.019)
Central Reserve City	-1.314 (0.082)	-1.089 (0.085)
Reserve City	-0.454 (0.040)	-0.311 (0.040)
ln(County Pop)	-0.083 (0.014)	-0.115 (0.014)
ln(County Manufacturing)	-0.011 (0.010)	-0.006 (0.010)
ln(County Cropland)	-0.039 (0.007)	-0.011 (0.007)

approach is implemented. Specifically, the Accept-Reject Metropolis-Hastings (ARMH) algorithm is used to estimate the model (Tierney, 1994; Chib and Jeliazkov, 2001). The priors on β are centered at 0 with a variance of 25 and the results are based on 10,000 MCMC draws with a burn in of 1,000. We begin by discussing the parameter estimates, then move on to prediction and model comparison.

The estimated coefficients shown in Table 11 demonstrate that bank size (measured by log (assets)), the ratio of bonds/assets, and Federal Reserve membership are positively associated with bank survival – findings that hold across both models. As shown in M_2, both eigenvalue centrality (measuring the importance of a bank's position in the network) and composite risk score (bank-specific risk) have a negative impact on bank survival. The negatively-signed coefficient on composite risk is quite intuitive and aligns with results found in numerous studies on bank survivability. The finding that a bank's position and importance in the network negatively influences survival is also intriguing. It aligns with Mitchener and Richardson (2019), which finds that, during the banking panics of the early 1930s, banks in reserve cities and central reserve cities faced significant withdrawal pressure from correspondent banks located in the hinterland. As shown above, centrality was concentrated in the major money centers: Chicago, New York, Kansas City, Minneapolis, St. Louis, St. Paul, Milwaukee, Philadelphia, and Cleveland. Thus, during panics, a prominent position in the network meant exposure not only to time and demand deposits withdrawals, but also interbank withdrawals, raising the probability of liquidity-induced suspensions. Lower probabilities of survivorship are also associated with the indicator variables for central reserve city and reserve city as well as county population.

Interestingly, the coefficient for a bank's ex ante contribution to systemic risk is positive and statistically different from zero. While individual bank risk and position in the network have a negative effect, higher systemic risk for a bank in 1929 increases the probability of bank survival. This finding is interesting in light of the RFC's recapitalization program. Jesse Jones, Chairman of the RFC, noted that the bank-rescue agency paid particular attention to large institutions in deciding which banks to grant assistance (Jones, 1951) and, as mentioned previously, of the systemically riskiest banks in 1929 (shown in Table 4), 70% of them received RFC assistance. The result for systemic risk may point to the beginnings of the too-big-to-fail approach to banking crisis in the US.

The new measures employed in this paper not only provide us with interesting results, but offer inferential advantages over other systemic risk measures. Importantly, the measures developed in this paper are constructed from the raw data, as opposed to being the predicted outcome of a regression. Hence, we do not have additional layers of uncertainty in the model and we do not need to conduct any inferential adjustments. Other systemic risk measures, such as CoVAR and SRISK, are developed from regression output. And using such measures as covariates in a separate model would lead to generated regressor issues and require standard-error adjustments.

For model comparison and prediction, we focus on marginal likelihoods ($\ln f(y|M_1)$ versus $\ln f(y|M_2)$) and posterior model probabilities. Given that we are using ARMH, we can use the building blocks of that algorithm to compute marginal likelihoods, which follows from Chib and Jeliazkov (2001). The marginal likelihood for model k is given by

$$m(y|\beta_k, M_k) = \int f(y|\beta_k, M_k)\pi(\beta_k|M_k)d\beta_k \tag{14}$$

and is crucial for comparing models. An advantageous property of marginal likelihoods is that they provide a measure of *sequential out-of-sample predictive fit*, where the fit of observation i is measured with respect to the posterior density based on data up to i, without conditioning on observations after i (Choudhary et al., 2017). This feature allows the researcher to overcome the complications associated with conditioning on the entire data set or using subsets of the data for in-sample and out-of-sample analyses.

Table 12 presents the model comparison and prediction results, and shows overwhelming evidence in favor of M_2. In particular, the specification has a posterior model probability of nearly

Table 12: Model Comparison and Prediction Results for M_1 and M_2.

	M_1	M_2
Log-Marginal Likelihood	-15543.84	-15114.64
Posterior Model Probability	3.99×10^{-187}	≈ 1
Hit rate	64.57%	66.79%

1 in comparison with M_1. The data heavily support the specification with the three additional measures (*Eigenvalue Centrality*, *Composite Risk Score*, and *SysRisk Percentage*). Additionally, the model strongly out performs M_1 at predicting the probability of bank failure.

While the marginal likelihood is the superior measure for out-of-sample prediction, the in-sample hit rates give us straightforward and intuitive numbers. M_1 has a hit rate of 66.79%, whereas M_2 has a hit rate of 64.57%. With the inclusion of network and composite bank risk measures, outcomes for 548 additional banks are correctly predicted. Overall, these new variables constructed from bank correspondent networks have immense explanatory power when it comes to specifying the probability of bank failure during the Depression. Further, these results point to the importance of including network variables and risk characteristics in analyses aimed at understanding bank survivorship during crises and support recent research in modeling systemic risk. Even ignoring the predictive ability of the model, the probit analysis shows that network position was an important determinant of bank failure in the crisis.

6.2 Robustness Check using National Bank Sample

To obtain results for our full sample, we coded exits as both mergers and failures, but these are clearly different outcomes. We lack this type of detailed information on survival outcomes of state banks; however, for national banks, we are able to further distinguish between types of exits using data from the *Annual Report* of the Comptroller of the Currency (1929-1934).

To do so, we again use two models with covariates that are the same as M_1 and M_2 in the previous section. However, the outcome variable is now ordered and defined as:

$$y_i = \begin{cases} 3 & \text{Bank Survives} \\ 2 & \text{Bank Merges} \\ 1 & \text{Bank Fails,} \end{cases} \tag{15}$$

and $\varepsilon \sim N(0, \sigma^2)$, i.e., an ordered probit model.[23] Location and scaling restrictions of this model

[23]The analysis was also completed with four ordered outcome categories – survive, merger/consolidation, distressed merger (bank absorbed or succeeded), failure – and the results do not vary from the presented case.

Table 13: Estimation, Model Comparison, and Prediction Results for the ordered probit models M_1 and M_2 with the sample of national banks. Posterior means and standard deviations (in parenthesis) are presented.

	M_1	M_2
Intercept	0.178 (0.087)	0.275 (0.088)
Loans/Deposits	-0.065 (0.037)	-0.170 (0.044)
Bonds/Assets	0.925 (0.105)	0.740 (0.110)
ln(Assets)	0.175 (0.014)	0.122 (0.016)
Eigenvalue Centrality		-5.950 (2.417)
Composite Risk Score		-0.069 (0.003)
SysRisk Percentage		2.398 (0.601)
Central Reserve City	-1.132 (0.160)	-0.925 (0.167)
Reserve City	-0.342 (0.079)	-0.153 (0.082)
ln(County Pop)	-0.045 (0.027)	-0.064 (0.027)
ln(County Manufacturing)	0.006 (0.019)	-0.001 (0.020)
ln(County Cropland)	-0.030 (0.012)	-0.016 (0.012)
Log-Marginal Likelihood	-7961.50	-7664.31
Posterior Model Probability	1.03×10^{-129}	≈ 1

are done by fixing the cutpoints, which are the parameters that relate the observed outcomes to the unobserved latent utility scale. The models are estimated by Gibbs sampling methods (Algorithm 3 in Jeliazkov et al. (2008)), and the MLE parameter estimates align. The priors on β are centered at 0 with a variance of 25 and the results are based on 10,000 MCMC draws with a burn in of 1,000. Marginal likelihood calculations follow from Chib (1995) and Jeliazkov et al. (2008).

Table 13 shows that the coefficients for our network measures are similar to those for the full sample; we observe negatively-signed effects that are statistically different from zero for eigenvalue centrality and composite risk score, and a positively-signed effect for a bank's contribution to systemic risk. Again, by comparing the marginal likelihoods, we see overwhelming support for M_2, with a posterior model probability of nearly 1. These results align with the previous section and point to an additional important implication: a specification including our new measures not only improves the prediction of bank failures, but also those for bank mergers, an important observed outcome in most financial crises.

7 Conclusion

Using a new, hand-collected data set of correspondent linkages for all commercial banks, we analyze systemic risk and network features on the eve of the Great Depression. We then assess how the largest banking crises of 20th century altered banking network properties and the concentration of risk. Systemic risk is modeled as a function of the interconnectedness and the credit quality of financial institutions in the system, which we combine to produce a single measure of systemic risk. We show that the pyramid-shape of the interbank network concentrated risk in particular nodes and made the banking system in 1929 more fragile and prone to contagion risk. We find that the resulting failure of over 9,000 banks increased systemic risk by 33%. Further, the banking crises caused risk to become more concentrated. The 10 systemically-riskiest banks increased their share of overall risk by 5 percentage points between 1929 and 1934.

Our analysis of the Great Depression also shows how much more damaging the crisis would have been if more systemically-important banks had failed. For example, if the 10 systemically riskiest banks in existence in 1929 subsequently failed, systemwide risk would have risen by more than 50%. On the one hand, the system showed some resiliency. Failures were concentrated in small and medium-sized banks. Centrally-located banks in the network had a higher predicted probability of failure, but the most systemically important banks were able to weather heavy depositor withdrawals during panic periods. They entered the Great Depression relatively healthy – with below average credit risk. They flexed but, in general, did not break (fail). Of the 20 systemically riskiest banks in 1929, only one failed, increasing systemic risk by only 1.59%. On the other hand, the Fed's reluctance to act as a Lender of Last Resort (Friedman and Schwartz, 1963) and the pyramid-shape of the banking system, meant that the largest and most central banks in the system (those in New York City and Chicago) met heavy depositor withdrawals during panic periods by contracting lending, leading to a more severe decline in economic activity during the early 1930s (Mitchener and Richardson, 2019).

The findings from our micro analysis of the Great Depression suggest that modeling banking networks has the potential to improve our understanding of where risk is concentrated before a crisis occurs and to predict where subsequent distress might center. Using bank-level data for the entire commercial banking system in 1929, we are able to identify useful predictors of subsequent financial distress. Bayesian model comparison and prediction show that bank-specific network centrality, composite risk, and a measure for the bank's contribution to systemic risk significantly enhance a probit and ordered probit model's ability to predict bank failures and bank mergers; we capture over 500 more survivals/failures occurring between 1930–33 when these variables are included. Both position in the network and composite risk are negatively related to bank survival.

However, a bank's systemic risk contribution appears to have increased survivorship. Given the RFC's intervention into the banking system in 1932, this finding points to perhaps early use of too-big-to-fail policies to influence financial institution survivorship in the U.S. financial system.

Finally, our research sheds light on similarly-motivated research on the GFC. By investigating a historical crisis and modeling network importance, we complement existing work in showing where risk may lie in the network. SRISK models (see Acharya et al. (2012); Brownlees and Engle (2017)), emphasize common risks across financial institutions' balance sheets, such as housing-sector assets during the GFC, as a source of risk. Our findings suggest that bank specific idiosyncratic risk and network position are also important variables of systemic risk and that they determine subsequent survivorship. In terms of our methodology, this is reflected in the fact that model selection places substantial weight on individual bank composite risk and centrality, which mattered because smaller banks relied on more central banks for business services and for satisfying regulatory requirements on reserves (e.g., interbank deposits). Our results for the Great Depression therefore complement the properties of SRISK in the GFC.

A large macro shock may have different effects on the financial system depending on the structure of network connections. Brunetti et al. (2017) examine correlation and physical networks of banks in Europe through the GFC and find that increases in correlation network connectivity presage financial crises and increases in physical network connectivity forecast liquidity problems. Our work using physical bank networks complements these findings for the Great Depression, and also show that physical network metrics are able to predict bank failure. Therefore, the uniqueness of the network during the Great Depression and the geographical dispersion of bank failures offer new insights into the analysis of systemic risk during crises, especially as the number of financial institutions in the Great Depression was far higher than that exists in recent times. The nature of economic crises may change over decades, but the value of network analysis in measuring and predicting systemic risk and its fallout remain robust across time.

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