Systemic Risk and the Great Depression

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Abstract

Employing unique hand-collected data on correspondent relationships for all U.S. banks and a methodology that captures bank credit risk and network position, we study how roughly 9,000 bank failures altered the network of financial institutions during the Great Depression. We show that the crisis raised systemic risk by 33%, with much of this increase concentrated at the largest banks, and that network density amplified the downturn. In particular, the pyramid-like network topology increased the system's fragility and risk-spreading propensity, resulting in an additional 255 bank failures. Our measure of systemic risk is also a strong predictor of individual bank survival during the 1930s. Further, systemic risk increased (decreased) the probability of bank survival for Federal Reserve members (nonmembers), and 278 more banks would have survived the banking crisis had all commercial banks been required to join the Fed. Branch-banking dampened the positive effect on survival stemming from a bank's central position in the network.

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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 mechanism 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 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 policymakers. 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.

To shed further light on these issues, we analyze how the largest financial crisis of the 20^{th} century—the Great Depression—altered the network of financial institutions in the United States. The topology of the network, the geographical distribution of risk, and the network positions of the thousands of failed banks during the early 1930s are unlike those of the Great Recession. Hence, our analysis draws attention to how these features of networks impact banking crises and systemic risk measurement. 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 approaches that estimate financial linkages from financial flow data or price and return co-movements, our measure of connectedness

[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).

uses stated bank correspondent relationships based on historical bank records.

We use these novel, hand-collected data as well as balance-sheet information on every networked commercial bank to develop measures of individual bank risk and systemwide risk before and after the banking crises of the early 1930s. Our systemic risk measure incorporates the credit risk of an individual bank as well as its position in the network. Our unique data and methodology allow us to examine where risk resided in the network, how much of it was concentrated in the largest banks in the system, and how the failure of roughly 9,000 banks between 1930–33 altered risk within the system. Further, 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. Finally, our microeconomic data on all commercial banks in the system allow us to analyze how our 1929 network measures of connectedness and systemic risk affect the probability of surviving the Great Depression and provide a novel test as to whether the inclusion of network-based systemic risk measures improves model prediction of bank failure.

We find that the massive banking crisis of the early 1930s reshaped the network, raising systemic risk per bank by 33%. Large banking crises, such as the Great Depression, appear to have enormous effects on systemic risk, validating the importance of tools for systemic risk measurement such as what we develop in this paper. However, knowing how a crisis affects an average bank's systemic risk requires mapping the network relationships for the entire banking system, not just the largest banks, as has been common in studying the Great Recession. Our comprehensive dataset includes all US commercial banks and our methodology permits us to compute average results as well as bank-specific measures of systemic risk, enabling us to develop a set of previously unknown facts and counterfactuals about the banking crisis of the Great Depression.

Our results show that the banking crisis of the Great Depression redistributed risk, increasing the contribution coming from 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. For example, Continental Illinois, which was the most connected bank in 1929, saw thousands of its connections wiped out; however, because the crisis made its balance sheet riskier, Continental's systemic risk increased. The finding for this particular bank reflects a broader and previously unearthed fact about the Depression: while the network on average became less connected as a result of the banking crises and the failure of thousands of banks, as a whole, risk emanating from the balance sheets of surviving banks actually increased.

Further, using our bank-level data set, we are the first to demonstrate that the pyramid-like structure of the commercial banking system, which had evolved in 19th century but persisted through the start of the Depression, had direct consequences for systemwide risk. Relative to random graph and bootstrapped scale-free network topologies, the 1929 bank pyramid-shaped topology exhibited a higher fragility and a greater propensity for spreading risk as it concentrated banking interactions at particular nodes in the network. And, during panic periods, the pyramid shape of the network left positionally-important banks (e.g., reserve and central-reserve city banks) exposed to large clusters of banks making simultaneous withdrawals through the correspondent network in order to fend off local runs a feature that magnified systemwide risk. We show that if the 1929 network had, instead, been a random graph network, 255 additional banks would have survived the Great Depression. This result supports recent theoretical work showing that interconnectedness can have a negative effect on systemic stability when networks are dense (Acemoglu et al., 2015) and draws attention to the importance of network topology in understanding where systemic risk emanates.

The 20 systemically riskiest banks in 1929 were largely the most connected, but had below average ex ante default risk. Only one failed, resulting in an overall increase in systemic risk per bank by 1.59%. While they were centrally connected and thus "systemically important," their better financial position and lower credit risk prior to the crisis allowed them to weather the storm of the Depression. That said, had all 20 of these banks failed, the crisis would have been much worse: systemwide risk would have risen by over 50%. Instead, the severe banking crisis of the early 1930s was dominated by the failure of small and medium-sized banks; on average, they had higher ex ante credit risk than their larger counterparts. The suspensions of the 30 largest banks during the Great Depression only increased systemic risk by 8.33%. The Depression represents a vivid example of a severe crisis that did not occur in the upper tail of the size distribution. These features of systemic risk stand in contrast to the Great Recession, a crisis dominated by large financial institutions, and draw attention to two additional contributions of our research. First, to be externally valid, systemic risk measurement tools need to account for crises that include all banks, not just the upper tail of the size distribution. Second, to understand why crises differ in terms of systemic risk outcomes, risk measurement tools need to capture both connectedness and default risk.

Using rich micro level data on individual banks, we also analyze how bank-specific information, network features, and regulatory characteristics of the banking market affect the probability of bank survival. We demonstrate that network position, systemic risk measures, and interactions involving the network significantly improve the sequential out-of-sample predictive fit of the model, obtaining a posterior model probability of approximately 1 and correctly classifying hundreds of additional bank survivals and failures. Further, we construct econometric models that allow us to consider how network and banking market characteristics affect the survivorship of individual banks during the Great Depression in order to explore drivers of distress that have not previously been tested in the literature. Our results show that a bank's ex ante systemic risk score lowers survivability during the Great Depression – consistent with theory and validation of our particular approach to risk measurement. We show that the impact of the network and systemic risk on the probability of bank survival vary greatly as one conditions on banks' geographical locations and institutional features. For Federal Reserve member banks, an increase in systemic risk increases the probability of survival. For nonmembers, an increase in systemic risk decreases the probability of survival. This finding has interesting implications for the wellspring of America's "Too Big To Fail" policies. We document that 95% of the top 200 systemic risk contributors in 1929 were Federal Reserve members. These banks were allowed access to the discount window, a particular advantage for banks located in the Atlanta Federal Reserve District, which were granted emergency liquidity during the panics of the Great Depression (Richardson and Troost, 2009; Ziebarth, 2013). However, regardless of location, and thus more generally, Federal Reserve member banks more than likely had improved survivorship because they often received large capital injections from the Reconstruction Finance Corporation (RFC). The RFC's chairman seems to have paid particular attention to large institutions in deciding which banks to grant assistance and to allow to be reopened after the banking holiday of March 1933 (Jones, 1951), which in the early 1930s, translated into well-connected Federal Reserve member banks. Indeed, had all non-member banks been able to join the Federal Reserve System prior to the start of the banking crisis of the 1930s, we estimate that, ceteris paribus, 278 additional banks would have survived the Great Depression. We also show that a central position in the correspondent network was often advantageous. However, the effectiveness of the correspondent network diminishes as the amount of branch banking in an area increases, thus demonstrating the network tension between branching and correspondent systems.

The findings in this paper relate to the literature on systemic risk measurement and the evaluation of crises. Early-generation systemic risk measures estimated network linkages using financial flow data. For example, Billio et al. (2012) construct networks of financial institutions using bivariate Granger causality regressions based on inferences from asset returns. Our analysis draws attention to physical connectedness, which has been explored more recently by Burdick et al. (2011) and Brunetti et al. (2019) for U.S. and European banks, respectively, during the 2007-08 crisis. Our paper adds to the literature on systemic risk measurement in several additional ways: we construct the before and after network to assess how crises reshape systemic risk, illustrating this for a period other than the GFC, and compare the pyramid-shaped correspondent banking network in existence in 1929 to other network structures in order to demonstrate how topology can predispose networks to additional risk. We examine the entire U.S. banking system at the bank level, rather than for a subset of publicly-traded institutions, enabling us to examine how, as a result of a crisis, risk moves across space and to demonstrate that systemic risk measures improve model prediction of bank failure – an important finding for policymakers. Clearly, graph-theoretic models would have been useful in the prediction of bank failure in the Great Depression. Thus, we provide a complete view of how banks were networked, why it mattered for the Great Depression, and how the network interacted with regulatory and legal systems.

Our paper also contributes to the fast-moving, complementary literature evaluating financial networks in earlier periods, which includes research on the national banking era

(Anderson et al., 2019; Calomiris and Carlson, 2017; Brownlees et al., 2017; Dupont, 2017), the founding of the Federal Reserve (Carlson and Wheelock, 2016, 2018; Anderson et al., 2018), and the 1930s (Richardson, 2007; Heitfield et al., 2017; Mitchener and Richardson, 2019). Our paper is the first to map the entire correspondent network of commercial banks (both member and nonmember banks), before and after the banking crises of the Great Depression, allowing us to show how banking distress changed network relationships and to compute measures of systemic risk for all commercial banks for the largest U.S. financial crisis of the 20th century. Although previous studies have emphasized the role of individual banks or groups of banks in precipitating banking panics (e.g., Friedman and Schwartz (1963) and Wicker (1996)) and the role of fundamentals in explaining subsequent distress (Calomiris and Mason, 2003; White, 1983), our research breaks new ground by quantifying where bank-specific risk resided prior to the start of these panics for all banks in the network and how institutional features and policies – such as branching systems, Federal Reserve membership and rescue packages – shaped systemwide risk and subsequent bank survivorship conditional on a bank's position in the network.

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 do not permit quantification of 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 (approximately 16,500 banks) so that we could analyze

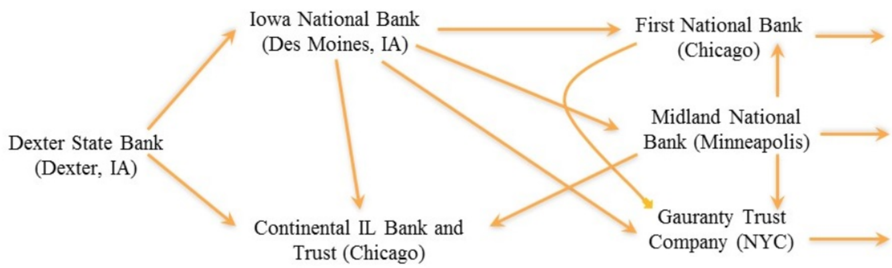

Figure 1: Illustrating correspondent relationships.

how the system changed as a result of the banking crisis of 1930-33.[3] 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 (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 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 (i.e., no adjustments are made for differences in flow).

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

3 The Correspondent Banking Network

We begin by describing the contours of the network just prior to the Great Depression. In July 1929, 25,144 respondent banks and 3,602 unique correspondent banks existed. Our data set contains the complete list of relationships between these financial institutions. 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 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 $A(i, j) = 0$. Since the correspondent-respondent relationship is directional, A is not symmetric, $A(i, j) \neq A(j, i)$. The total number of links in the network is 70,679. In examining their distribution, most respondent banks have very few correspondents. On the other hand, correspondent networks can be very large – in the thousands – a feature that has implications for the shape of the network. Figure 2 plots the locations of correspondent and respondent banks. 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 number of connections (degree) of the node and is plotted in blue color. Respondents are in red. 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. Correspondent banks appear to be located in larger cities.

As has been well documented by economic historians, waves of banks failures between

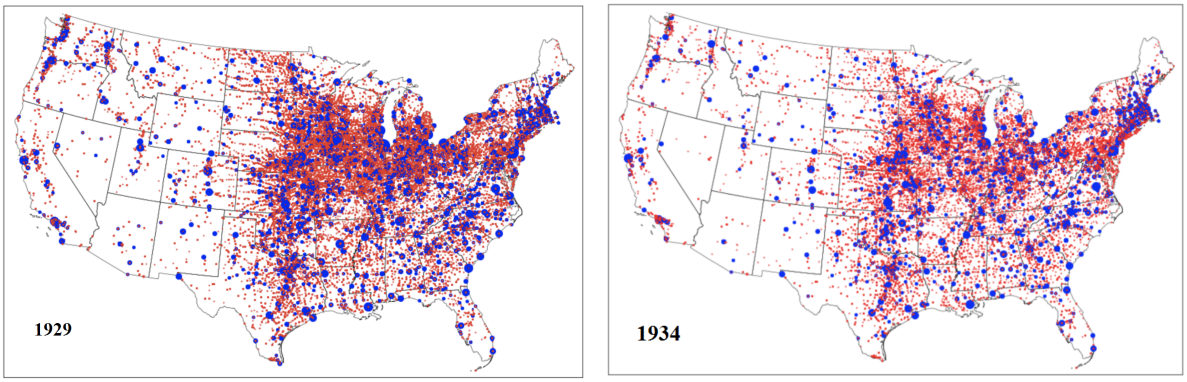

Figure 2: Respondent banks in red and correspondent banks in blue, sized by relative degree of each bank for 1929 and 1934. Respondent banks place money with correspondent banks. Correspondent banks are plotted in blue and have points that are two times 1 plus the natural logarithm of the node's degree. The plot in the left is for 1929 and the one on the right is for 1934.

1930–1933 irrevocably altered the US financial system.[4] Distress occurred throughout the country, but especially in rural areas and smaller towns. Figure 2 shows how the network changed in response to the more than 9,000 banks that exited the system. Between 1929 and 1934, the number of banks in the network declined by 36%, from 25,684 in 1929 to 16,446 in 1934 and the number of correspondents fell by 41% (from 3,602 to 2,134).The total number of links in the network fell by 41%, from 70,583 in 1929 to 41,313.

3.1 Network Statistics

3.1.1 Theory and Examples

In this section, we introduce network and systemic risk measures that are employed to understand the 1929 and 1934 networks, and the changes occurring between these two dates. We begin with a simple example network in order to obtain a better understanding of network topology and its relation to our systemic risk metric. Figure 3 shows a network of just 6 banks (nodes) and 15 links. It is a directed network, so that a relationship can run both ways, and the network is unweighted to correspond to the dataset in the paper, i.e., all links have unit weight and point from the bank placing money (the respondent) to the one receiving it (the correspondent). Some links are uni-directed and have one arrowhead and

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

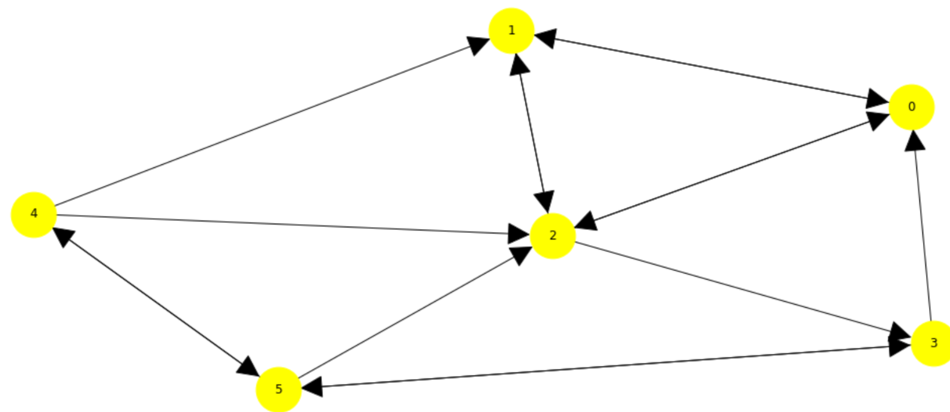

Figure 3: A network of 6 nodes and 15 links.

others are bi-directed and have two arrowheads. Nodes are numbered from 0 through 5.

The network may be represented by an "adjacency matrix" shown in equation (1). The matrix shows which bank on the rows connects to which bank on the columns. (Banks are numbered 0 through 5.)

$$A = \begin{bmatrix} 0 & 1 & 1 & 0 & 0 & 0 \\ 1 & 0 & 1 & 0 & 0 & 0 \\ 1 & 1 & 0 & 1 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 1 \\ 0 & 1 & 1 & 0 & 0 & 1 \\ 0 & 0 & 1 & 1 & 1 & 0 \end{bmatrix} \quad (1)$$

Understanding which nodes have the greatest influence in the network, i.e., those that are the most critical, is of particular interest to policymakers who might want to identify "too big to fail" or systemically important financial institutions (SIFIs). To understand this feature of our network, we use several variants of the most common measure, centrality: degree, eigenvector centrality, and betweenness centrality.

Degree: Centrality can be measured by the number of connections a node has, i.e., its "degree." Of course, degree centrality ignores the fact that a node with few connections may still have a huge influence if it is connected to a node with many connections.[5] Degree centrality may be varied by computing degree to a chosen depth, say three levels deep, a

[5]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.

parameter chosen at the discretion of the modeler.

For the six nodes in our example network, the degrees are $\{5, 5, 7, 4, 4, 5\}$ for a total of 30 (twice the number of links, 15, because each link adds a degree to two nodes). We see that node #2 has the greatest degree. Each node's degree can be apportioned into in-degree (links coming in) versus out-degree (links going out). In the context of the paper, we may think of nodes with a greater proportion of in-degree as correspondent banks and nodes with greater out-degree proportion as respondent banks.

Eigenvector centrality is a more general formulation (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 adjacency matrix, A. This leads to a circular system of n simultaneous equations:

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

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

$$\lambda c = A \cdot c \tag{3}$$

where λ is a scalar quantity, c is a vector of size n, and as before, $A \in \mathcal{R}^{n \times n}$. Equation (3) 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.

A computation of eigenvector centrality for the example network gives the following result for the six nodes: $\{0.5727, 0.5034, 0.5493, 0.2982, 0.0653, 0.1541\}$. Notice that node #0 has the highest eigen vector centrality even though node #2 has the highest degree. The first three nodes derive their influence from their position in the network relative to the other nodes. They have relatively more in-degree.[6] Since the banking network in the Great Depression was known to be pyramidical, nodes with a higher extent of in-degree will be higher up in the pyramid.

[6]For example, this is how researchers define the importance of a web page in the Google search algorithm, where pages with a large number of links pointing to them are more important.

Betweenness centrality 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 of a node is a function of the number of shortest paths in the graph that pass through that node. Following Freeman (1977), betweenness centrality for a node v is defined as follows:

$$b_v = \sum_{i,j} \frac{g(i,v,j)}{g(i,j)} \tag{4}$$

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 $i \neq v$.

The betweenness centrality for the nodes is $\{1.5, 0.5, 8.0, 6.5, 0.5, 5.0\}$. Notice that the ordering is different than what we obtain from eigenvector centrality. This is to be expected, since betweenness centrality assigns greater relevance to nodes that are intermediaries in the network. Nodes at the top of the pyramid, while important, are less likely to be intermediaries. We will see this distinction between eigenvector and betweenness centrality in the empirics that follow.

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

$$\begin{aligned} S &= \frac{1}{n} \cdot \sqrt{R^\top \cdot A \cdot R} \\ &= \sqrt{\frac{R}{n}^\top \cdot A \cdot \frac{R}{n}} \\ &= \sqrt{Q^\top \cdot A \cdot Q} \end{aligned} \tag{5}$$

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. Since the elements of R and A are all non-negative, $S \geq 0$.

Equation (5) 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. The systemic risk measure, S, may be thought of as a network-weighted measure of composite credit risk in the banking system. If there are no network linkages, then A is a zero matrix and $S = 0$.

We examine how this systemic risk score changes with risk levels, R. Assume that bank i can either have low risk ($R_i = 1$) or high risk ($R_i = 2$). If all banks were low risk, the vector of credit quality is $R = [1, 1, 1, 1, 1, 1]$. Using this vector, we compute a lower bound for systemic risk, i.e.,

$$S = \frac{1}{n}\sqrt{R^\top \cdot A \cdot R} = 0.6455$$

But if all banks were high risk, i.e., $R = [2, 2, 2, 2, 2, 2]$, then the systemic risk per bank would be 1.2910 (an upper bound, assuming no change in network structure). This is exactly double because the function $S(R, A)$ is linear homogenous in R. These values are the lower and upper bounds for S. We can examine the effect of increasing the risk of banks with low eigenvector centrality, i.e., letting $R = [1, 1, 1, 2, 2, 2]$, in which case $S = 0.9428$. But, if we raise the risk of high centrality banks, then $R = [2, 2, 2, 1, 1, 1]$ and $S = 1.0274$, as expected. Both these values lie between the upper and lower bounds computed earlier.

Changes in the number of banks. Only two-thirds of the banks survived over the period 1929-1934. Bank failures change the network and systemic risk, S, may increase or decrease depending on the centrality and credit quality of the failed banks. For example, suppose all banks are high risk, i.e., $R = [2, 2, 2, 2, 2, 2]$ and $S = 1.2910$. If a high centrality bank exits (e.g., assume node #2), then we eliminate it from the adjacency matrix, A, and the credit score vector, R, and recompute S, which in this case, falls to $S = 1.1314$. This is understandable because, ex post, the removal of a hub bank makes the network less susceptible to risk spreading, leading to a lower systemic risk score. If the infected bank remains in the system and has a higher (riskier) credit score, then, of course, S would increase. In the ensuing empirical analyses, we present such effects as well. On the other hand, if a less central bank (say #4) were removed, systemic risk would increase to $S = 1.3266$ because more weight ends up at the central nodes. This example explains some of the empirical results we see when comparing the network in 1929 and 1934.

S is an appropriate measure for our historical setting because: (1) it captures both connectivity risk and credit risk; (2) it properly accounts for the directions of the correspondent-respondent relationships because A is not symmetric; (3) the functional form of S is linear and homogeneous which allows us to decompose the measure bank-by-bank and compute individual bank contributions; and (4) it has attractive properties for prediction. Because S is constructed from raw data matrices, as opposed to being the result of regression output, it can be easily employed for prediction exercises without issues of estimation uncertainty. Additionally, the properties of S align with the literature on systemic risk during crises. Acemoglu et al. (2015) show that when the number of negative shocks in an economy are large, highly connected network structures can be a source of systemic risk and instability. As we showed in the theory and examples, as network connections in A increase, so does our systemic risk score, S. Therefore, S captures the movement in systemic risk that would be expected in crisis periods. Before describing S for the 1929 and 1934 networks (Section 4.2), we detail the network topologies in the following sections.

3.1.2 Clusters, Degree, and Power Laws

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 was almost fully connected in 1929. The remaining 30 components have sizes of 22, 12, 9, 6, and the rest have four nodes or less.

For 1929, the mean degree of nodes in the network is 5.50 with a standard deviation of

49.60.[7] The median degree in the network is 3.0. The "degree distribution" of the nodes is shown in Figure 4 for both 1929 and 1934. The left plots show nodes with degree less than 50 while the right plots show nodes with degree greater than 50. The distribution is extremely skewed: there are a large number of nodes with low degree and a few nodes with very high degree.[8] We can also examine the degree distribution by plotting the (log) number of nodes against the (log) number of links (degree). The left panel of Figure 5 shows a log-log plot of the network in 1929, where extreme nodes with degree greater than 50 have been excluded. The quasi-linear and negative relationship of the log-log plot and the power law coefficient ($\alpha = 1.65$) suggest bank nodes exhibit the usual shape, slope, and power law distribution characteristic of social networks (Barabasi, 2002; Barabasi and Bonabeau, 2003; Gabaix et al., 2003). Further, the node distribution can be compared to the asset size distribution of banks in 1929. The right panel of Figure 5 shows a similar shape and slope as the degree distribution; however, the power law is lower ($\alpha = 1.17$). To a large extent, the most well-connected banks are also the largest banks, fitting the modern policymaker's definition of "systemically important".

By 1934, the number of clusters (disjoint groups) had fallen 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 in the network falling from 3 in 1929 to 2 in 1934, 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 $\alpha = 1.60$. We also examined whether the network was different in 1934 versus 1929, by comparing the degree distributions in both years using a Kolmogorov-Smirnov statistic. The K-S statistic is 0.1022 with a p-value of 0.0001, i.e., indicating that network structure changed significantly from 1929 to 1934, a result we explore in more detail below.

[7] 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.

[8] 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).

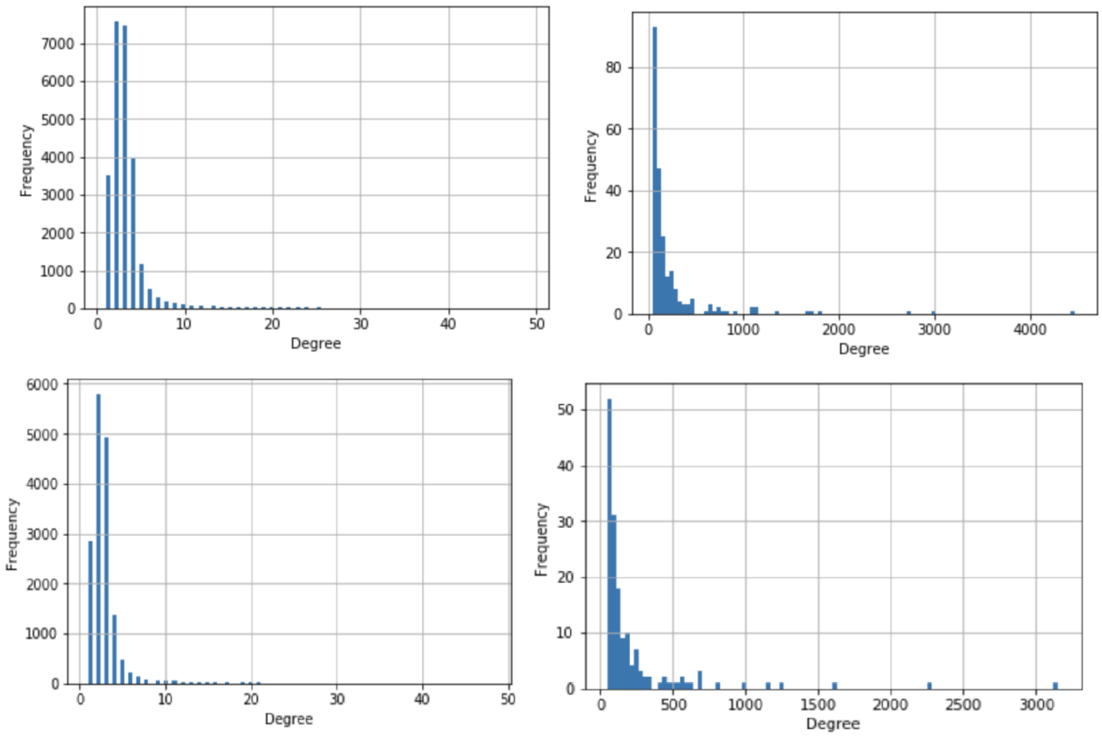

Figure 4: Degree distribution in 1929 (upper plots) and 1934 (lower plots). The left panels plot nodes with degree less than 50 while the right panels plot nodes with degree greater than 50.

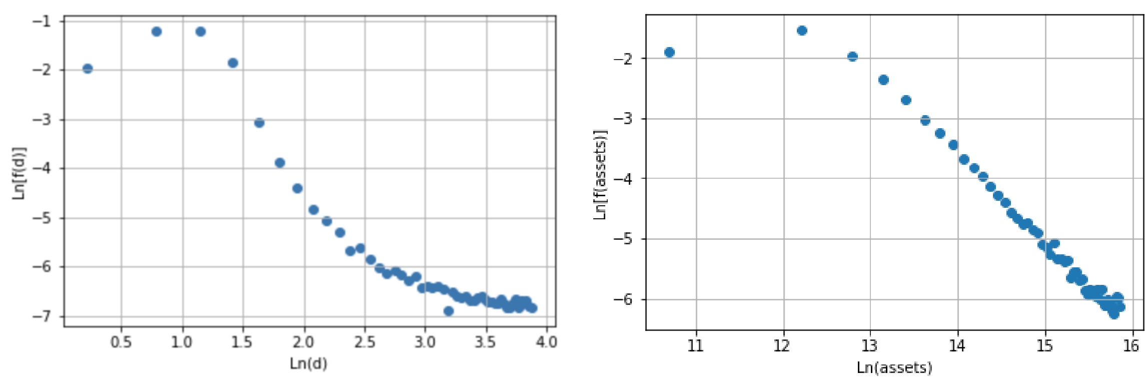

Figure 5: Network Density and Assets. Log-log plot of the degree distribution in 1929 excluding extreme nodes with degree greater than 50. We plot log degree on the x-axis and log of the density function on the y-axis. For power-law densities, the function is $f(d) = d^{-\alpha}$. Taking logs we have $\ln[f(d)] = -\alpha \ln(d)$. The power law coefficient is $\alpha = 1.65$. The second plot shows the same for bank asset levels, with a power law coefficient of $\alpha = 1.17$.

Table 1: Top 10 banks by eigenvalue centrality (normalized), along with their degree.

1929: Bank Name and Location	EigenCent	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
1934: Bank Name and Location	**EigenCent**	**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

3.1.3 Centrality

The banks with the highest eigenvalue centrality measures in 1929 and 1934 are shown in Table 1. In 1929, Continental Illinois Bank and Trust (Chicago) had the most linkages in the network, with 4,474 in 1929. Chicago experienced two pronounced banking panics in 1931–32, and 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 and moved from second to first overall, in both degree and eigenvalue centrality. In examining the eigenvector centrality scores, it is clear that the centrality of the top banks increased from 1929 to 1934. Both before and after the banking distress, six of the top 10 banks with the highest degree centrality are located in the financial centers of New

Table 2: Top ten banks by betweenness centrality.

1929: Bank Name and Location	1934: Bank Name and Location
1. First National Bank of Chicago (Chicago, IL)	1. First National Bank of Chicago (Chicago, IL)
2. Security First National Bank of Los Angeles (Los Angeles, CA)	2. Security First National Bank of Los Angeles (Los Angeles, CA)
3. Union Trust Company (Cleveland, OH)	3. *First National Bank in St. Louis (St. Louis, MO)*
4. American Trust Company (San Francisco, CA)	4. *The Pennsylvania Company (Philadelphia, PA)*
5. Citizens National Trust & Savings Bank (Los Angeles, CA)	5. *Republic National Bank and Trust (Dallas, TX)*
6. Mississippi Valley Merchants State Trust Company (St. Louis, MO)	6. Mellon National Bank (Pittsburgh, PA)
7. Mercantile Commerce Bank and Trust Company (St. Louis, MO)	7. Mercantile Commerce Bank and Trust Company (St. Louis, MO)
8. Fifth Third Union Trust Company (Cincinnati, OH)	8. *The Boatmen's National Bank (St. Louis, MO)*
9. Mellon National Bank (Pittsburgh, PA)	9. *Harris Trust and Savings Bank (Chicago, IL)*
10. The Philadelphia National Bank (Philadelphia, PA)	10. *City National Bank and Trust Company (Chicago, IL)*

York City and Chicago. These two cities were known as central reserve cities since banks that were not members of the Federal Reserve System could satisfy their state-mandated reserve requirements by holding reserves in banks located in these cities. The other four on the list are in reserve cities of the Federal Reserve System. As discussed in the next subsection, reserve and central reserve cities gave rise to a correspondent network with a pyramid-like structure.

Interestingly, but consistent with the example from Section 3.1.1, the results differ when considering betweenness centrality. Only one of the top 10 banks using this measure is 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, for betweenness centrality, the most influential connector nodes are coast-to-coast and geographically dispersed. Further, using this measure, there is far less stability in the top 10, with only four banks from 1929 appearing in 1934 (new entrants are shown in italics in Table 2). The greater degree of temporal change in betweenness centrality, relative to the other centrality measures, likely reflects the fact that the banking crisis was widespread. That is, even in 1929, many of the most influential banks were located outside of the central reserve cities.

3.2 The Pyramid Structure of the Banking Network

Financial historians provide us with some priors about the general topology of the networks in 1929 and 1934 – features that evolved out 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, an aspect not previously examined by researchers, 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] By 1929, however, only 10% of state-chartered commercial banks had joined the Federal Reserve System. Most small and medium-sized banks in the financial system did not join and satisfied their reserve requirements by keeping them in Fed-member banks.[11] Interbank deposits thus constituted a significant share of Fed-member bank deposits: for every dollar of demand deposits, Fed member banks held $0.25 of interbank deposits.[12]

The fact that substantial amounts of highly liquid interbank deposits were held in other banks has important implications for the correspondent network's role during banking crises. In the 19th century, withdrawals from non-central reserve city banks happened regularly, and if they were sufficiently large, they could put pressure on call loan rates to rise and stock

[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), Carlson and Wheelock (2018), and Jaremski and Wheelock (2019).

[11]In June 1929, member banks held 93% of all interbank deposits in the United States. Nonmember banks held only 7%. In New York, for example, the 15 banks with largest number of correspondent-respondent relationships belonged to the Federal Reserve. This group included nine national banks (Chase, Chatham-Phenix, Chemical, City, Commerce, First, Hanover, Park, and Seaboard), and six state member bank and trust companies (Bankers, Chemical, Guaranty, Irvine, Manhattan, and New York). In Chicago, the banks doing a substantial correspondent banking business either belonged to the Federal Reserve, were owned by a national bank that belonged to the Federal Reserve (e.g., all of the stock of First Union Trust and Savings was owned by First National Bank of Chicago), or were combined with a national bank in a holding company or similar corporate structure (e.g., Continental Illinois was a holding company that controlled the Continental National Bank and the Illinois Merchant and Trust Company).

[12]The 8,707 member banks held $35.9 billion in total deposits, $18.7 billion in demand deposits, and $3.7 billion in interbank deposits. Interbank deposits exceeded 60% of aggregate reserves. 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.

prices to fall, triggering panic selling of assets and inducing a financial panic that could reach well beyond New York City.[13] Indeed, all of the major panics of that era were marked by withdrawals of funds by the country and reserve-city banks from New York City (Bordo and Wheelock, 2011). Even though the national banking system's reserve requirements created a large potential pool of reserves that could be used at the time of such a crisis, there was no central coordinating mechanism to deploy them. Rather, individual banks, wary of being run, tended to hoard them and feared paying penalties if they fell below the legal requirement. As a consequence, the national banking system's reserves, though large in aggregate, were effectively unavailable for meeting the demands of panicked depositors in crisis periods (Beckhart, 1922).

The introduction of the Federal Reserve System was meant to replace this fragile system, but it depended on banks joining the system and a willingness by Fed policymakers to deploy reserves to troubled banks in times of need.[14] During the early 1930s, when many banks frequently faced significant time and demand deposit withdrawals, they would turn to their most liquid assets to satisfy depositors' claims. The two most liquid assets most banks held were vault cash and interbank deposits. When just a few banks faced distress, the correspondent network could efficiently transfer funds from the center to places where banks were being run and satisfy the increase in demand for liquid funds. But, the system could become overwhelmed if say, during a panic, the demand for liquidity surged. During such panics positionally-important banks (e.g., reserve and central-reserve city banks) could face withdrawals from multiple respondents simultaneously. Network position and the correspondent banking network were thus critically linked during the 1930s, when banking panics featured prominently (Friedman and Schwartz, 1963; Wicker, 1996; Jalil, 2015). To a large degree, then, the pyramid-shaped network topology 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, and the subsequent failure of the Federal Reserve System to

[13] The standard story for explaining why country banks and reserve city banks withdrew their interbank deposits in this era was due to the seasonal demand for money arising from planting and harvest cycles (See Calomiris and Gorton (1991)). The creation of an elastic currency that could meet the needs of agriculture was a key principal behind the Feds founding.

[14] As Friedman and Schwartz (1963)famously argue, the Fed failed to adequately provide liquidity and, as noted above, most banks were outside the Federal Reserve System as of 1929.

convince all state-chartered banks to switch their charters and join the system after 1914. Though the broad contours of the correspondent network's topology are well documented, its contribution to systemic risk just prior to the Depression has not been previously analyzed.

To examine the properties of this network topology, and in particular how they relate to systemic risk, we compare the diameter and fragility of the pyramid networks to (i) a random graph network and to (ii) a bootstrapped scale-free network with approximately the same number of nodes and mean degree.[15] "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. In essence, it measures 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.[16] The bigger the diameter, the less likely it is 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: $F = E(d^2)/E(d)$, 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. Hence, if a highly centralized node is compromised, the propensity for risk to spread to the other nodes is high.

We begin with an example that illustrates the differences between a pyramid structure, a random graph, and a scale-free graph. Pyramid graphs are mostly tree-like even though they are not directed acyclic graphs (or DAGs). Topologically, pyramid graphs are scale-free and are likely to have degree (connections) concentrated in a few nodes; they are within the class of scale-free networks (Lasszlo-Barabasi and Albert, 1999; Barabasi and Bonabeau, 2003; Barabasi, 2002). Recall that the 1929 network contains 25,684 nodes and has a mean degree of 5.5. This pyramid network in 1929 has a diameter of 13 and fragility of 453. For comparison, we generated a random network with the same number of nodes and mean degree.[17] The random network specified in this manner has a diameter of 12 and a fragility

[15] A scale-free graph is one where the degree distribution is not Gaussian as in a random graph, but follows a power-law distribution; see Lasszlo-Barabasi and Albert (1999).

[16] Counterparty contagion is the specific form of contagion we are referring to here, as opposed to other forms, such as confidence effects.

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

of only 6.5. However, the more apt comparison is versus a bootstrapped scale-free network (rather than a random network) with the same mean degree and number of nodes. The bootstrapped scale-free network has a diameter of 14 and a fragility of 180, much higher than that of a random graph, but still much lower than the pyramid network, suggesting that risk was even more concentrated than we would expect in a scale-free setting.

The results are similar when we examine these measures after the banking crisis of the early 1930s. The network was reduced to 16,446 nodes, with a mean degree of 5.0. The diameter in 1934 is 13 and fragility is 354. A random network with the same number of nodes and same degree has a diameter of 12 and a fragility of 6.0. The bootstrapped scale-free network with these parameters has a diameter of 14 and a fragility of 149.

To shed light on how crises change financial systems, we can also compare how the diameter and fragility of the network changed with respect to the recent Global Financial Crisis (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, the diameter also 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. Between 1929 and 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 rose to 172 in 2006, and then dropped to 35 by 2009. System fragility during the GFC was thus considerably smaller than in the Great Depression, although some of this difference may be attributable to the fact that 2005-2009 calculations are based on a small sample of financial institutions.[18]

[18]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.

4 Quantifying Systemic Risk

4.1 Deriving Composite Risk Scores

We now turn to measuring systemic risk and develop empirical measures of both individual bank credit risk (R) as well as aggregate system-wide risk (S) that incorporate the interconnectedness of banks. In order to construct a measure of systemic risk rather than "systemic importance" (defined on only size and/or connectedness), it is necessary 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 or regional exchanges, we employ financial ratios on a best-efforts basis with limited data 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 measure of *systemic risk per bank*.

We begin with bank-level balance sheet and income data to derive bank-specific measures of 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 (due from banks);
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).[19]

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

$$C = a + \frac{1}{1 + BUF} \cdot b. \tag{6}$$

[19] 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). One might argue that retained earnings and equity are the same, but in a system of book value accounting, retained earnings are a good proxy for profitability.

So that C is bounded between 1 and 10, we set $a = -8$ and $b = 18$ because $BUF \in (0, 1)$. An increasing score implies greater risk. For the banks where the BUF data was missing we set these banks C values to the means of all banks. This does not change the first four moments of the distribution of C in any way. The mean credit risk score in 1929 is 5.02 (median 4.90), with a standard deviation of 1.92. Table 3 displays the credit risk scores and leverage ratios for the 10 largest banks in 1929 and 1934 (as measured by equity).[20] Interestingly, especially in comparison to the GFC, 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. Prior to the Depression, much of the balance-sheet risk within system thus resided in medium to smaller sized banks as evidenced by the average C for equity quintiles, which (from smallest to largest equity) are 6.27, 5.52, 5.09, 4.45, and 3.67, respectively. The risk measures for 1934 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. In 1929, whereas all of the largest banks had risk scores below the mean, this changed after the early 1930s: both National City Bank of New York and Continental Illinois exceeded the mean of 5.65 in 1934.[21]

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

$$L = \ln(1 + Assets/Equity). \tag{7}$$

We add 1 to the untransformed leverage in the equation above to handle cases where asset data are missing. For these banks, we set the value of L to the sample mean (less than 3% of the sample). This does not change the first four moments of the distribution of L in any

[20] In the table, Bank of America Nat. Tr. & Sav. Assn. (San Francisco, CA) in 1934 is related to Bank of Italy Nat. Tr. & Sav. Assn. (San Francisco, CA) in 1929. A.P. Giannini's original bank was the Bank of Italy, founded in 1904. In the 1920s, he established other institutions, which were later consolidated into Bank of America, part of the Transamerica holding company.

[21] As a caveat, we note that higher profitability may not necessarily mean lower risk as lucky banks that take more risk might be more profitable, as noted in Meiselman et al. (2018), who argue that it is possible that higher profits accrue to banks with higher beta. However, in crisis periods, this is unlikely. Another caveat is that higher leverage banks may just have better quality assets. However, for 1929 and 1934, the correlation between leverage and ROA (surplus profits divided by assets) is negative. If we treat surplus as a measure of how good the assets are, this suggests the opposite conclusion.

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

1929: Bank and Location	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
Top 10 mean	2.988	7.006
Population mean	5.020	7.976
1934: Bank and Location	**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
Top 10 mean	4.075	7.284
Population mean	5.651	6.421

material way.[22] Finally, we compute a composite risk score, R, which combines the inverse of profitability measure, C, and transformed leverage, L, such that:

$$R = C \times L. \tag{8}$$

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

[22] Appendix A.1 shows the improved performance of transformed leverage relative to untransformed leverage.

not assign them as such. Multiplying C by L compensates for this possibility. In 1929, R has a mean value of 10.54 and a standard deviation of 4.27. By 1934, the banking crises had raised the average riskiness of banks to 10.76 (with a SD of 4.29).

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.[23] 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 and 1934. In Appendix A.1, we compare R to several other ratios and measures of risk. We show that R outperforms the other measures at predicting default, and thus present systemic risk measurement results in the following sections employing R.

4.2 Systemic Risk Per Bank

Plugging the values from the 1929 data into equation 5, we find that the total systemic risk per bank, S, is 0.104. By itself, the value carries little meaning, but since it can computed at different points in time, the metric allows us to examine how overall risk in the system changes as a result of the banking crises of the Great Depression. By 1934, 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. We also undertook a bootstrap analysis to determine if the increase in S from 1929 to 1934 is statistically significant. Bank failures resulted in a large reduction in the number of banks in the sample from 25,644 in 1929 to 16,446 in 1934, i.e., a reduction of 9,238 banks. We simulated random removals of this number of banks from the 1929 network in order to examine how much the S score changes. This experiment was repeated 1,000 times, and we kept track of the difference in S score when banks were removed from the network versus the original score of 0.104. As expected, the mean difference is zero, with a standard deviation

[23] If we ignored the log specification in equation (7), i.e., $L = Assets/Equity$, then R would be equivalent to $\frac{Assets}{Equity+RetainedEarnings}$, which is a profitability-adjusted measure of leverage, akin to the Merton metric, which is a risk-adjusted measure of leverage.

of 0.004. Hence, the increase in S score from 0.104 in 1929 to 0.138 in 1934 is statistically significant, suggesting that large financial crises can dramatically influence systemic risk.

The 33% increase can be explained by the two components of our systemic risk measure. On average, balance-sheet risk (measured by R) increased between 1929 and 1934. From Table 3, we can see that credit risk for the largest banks increased nearly 3 times more than the average increase. While average connectivity (measured by mean degree) fell, the connectedness of the top banks increased (as seen from the eigenvalue centrality scores in Table 1). Therefore, our results suggest that connectivity and balance sheet risk are concentrating at the top of the pyramid network. To understand exactly where risk emanated from before and after the banking distress of the Great Depression, we can decompose our systemic risk measure into the risk contribution of each bank. 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*:

$$S = \frac{\partial S}{\partial Q_1} \cdot Q1 + \frac{\partial S}{\partial Q_2} \cdot Q2 + \ldots + \frac{\partial S}{\partial Q_n} \cdot Q_n. \tag{9}$$

Each partial derivative $S_j = \frac{\partial S}{\partial Q_j}$ multiplied by Q_j is the risk contribution of bank j. We can calculate all derivatives S_j in closed form using the following vector derivative:

$$\frac{\partial S}{\partial Q} = \frac{1}{2S}[A \cdot Q + A^\top \cdot Q] \in \mathcal{R}^n \tag{10}$$

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.

Table 4 shows the percentage of systemic risk contributed by each of the top 20 risk-contributing banks in 1929 and 1934. Comparing it to Table 1, we can see there is a considerable correspondence between the banks exhibiting the most systemic risk in 1929 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%. Comparing the 1929 values in Table 4 to those for 1934 reveals that the banking

Table 4: Top 20 banks by percentage contribution to systemic risk, 1929 and 1934.

1929: Bank Name and Location	Percentage Risk
Continental Illinois Bank and Trust (Chicago, IL)	3.23
Chase National Bank (New York City NY)	1.56
National Bank of the Republic of Chicago (Chicago, IL)	1.21
First National Bank of Chicago (Chicago, IL)	1.19
Commerce Trust Company (Kansas City, MO)	1.05
National City Bank (New York City, NY)	1.04
First National Bank (Minneapolis, MN)	0.97
First National Bank in St. Louis (St. Louis, MO)	0.85
Central Hanover Bank & Trust Company (New York City, NY)	0.76
Guaranty Trust Company (New York City, NY)	0.74
First National Bank of St. Paul (St. Paul, MN)	0.63
First Wisconsin National Bank (Milwaukee, WI)	0.62
National Stock Yards National Bank (National Stock Yards, IL)	0.61
National Park Bank (New York City, NY)	0.60
Mercantile Commerce Bank & Trust Company (St. Louis, MO)	0.59
Fletcher American National Bank (Indianapolis, IN)	0.46
Northwestern National Bank (Minneapolis, MN)	0.45
Union Trust Company (Cleveland, OH)	0.45
Fidelity National Bank and Trust Company (Kansas City, MO)	0.42
Drovers National Bank (Chicago, IL)	0.41
1934: Bank Name and Location	**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

crises of the early 1930s caused the concentration of risk in the network to rise for the top banks. In 1934, the 10 systemically riskiest banks contributed 17% to overall risk, while the top 20 contributed 23% of the overall systemic risk. Additionally, while Continental Illinois lost thousands of connections (Table 1), its balance sheet risk increased enough so that it remained the system's riskiest bank in 1934. These findings are important from a modern regulator's perspective since the network topology, number of failures, and location of the failures are unlike the GFC. From Section 3.1.1, we can see that the change in S due to exits in the network depends on the network position and credit risk of exiting banks. Since most of the network exits during the Great Depression were less positionally-important banks, we provide an additional perspective on how systemic risk changes due to a massive financial crisis.

As a robustness check, we also recomputed the risk score in equation (8) using size weights based on bank assets. That is, we redefined $R = C \times L \times w$, where w is an asset-based weight, such that if the bank was in the top 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.

4.3 Realized Bank Suspensions

For the most part, 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 systemically risky banks in 1929 (Table 4), Union Trust Company (Cleveland, OH), failed. Four others experienced suspended payments and subsequently experienced "distressed" mergers: National Park Bank (NYC), 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 and lower credit risk prior to the crisis allowed them to bend, but not break. Appendix Figure A.2.1 shows that most of the banks that exited the network between 1929 and 1934 were smaller than the median-sized bank, as measured by total assets.

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 20 risk contributors received a large capital injection from the RFC. This suggests that regulators, even then, implicitly understood the nature of risk in networked financial systems.

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.[24] 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).[25] These 30 suspensions accounted for a total of $1.8 billion or 25% of the nation's loans and investments in suspended commercial banks.

To compute how the failure of these banks altered systemic risk, we set the risk score R for these banks to the maximum value, recompute S, and look at the percent change in S. Risk in the system should then rise through each bank's relationships to other banks in the adjacency matrix. The top 10 suspensions by total assets and their percent change in systemic risk are shown in Table 5. Although the Great Depression wiped out an inordinate number of banks, systemic risk arising from the realized suspensions of the 30 largest banks

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

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

Table 5: 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 (New York City, 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

only increased by 8.33%. However, their composite risk score was well-above the average for their large size in 1929 and many of them were not members of the Federal Reserve System, which is fairly unusual for banks with their high degree. Foreshadowing, our econometric analysis in Section 5 suggests that banks with these characteristics in 1929 were more likely to subsequently fail by 1934.

4.4 Counterfactuals

An important question from a regulator's perspective is how overall systemic risk changes if something happens to one of the systemically riskiest banks. Our model allows us to consider the effects of counterfactuals that affect systemic risk. We consider two: (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. Therefore, when a bank exits, system-wide risk falls by approximately the same amount that the bank contributes 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.[26] 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. To illustrate, consider Continental Illinois – the systemically riskiest bank by our methodology. If this bank is quarantined, risk falls by 3.2%. Likewise, in 1934, if Continental Illinois were quarantined, systemic risk would fall by 4.21%. 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%.

A second counterfactual of interest considers how the hypothetical failure of an ex ante systemically important bank affects overall systemic risk. We can simulate the failure of the 10 systemically riskiest banks by setting their risk score, R, equal to the maximum risk score across all banks in 1929. Appendix Table A.3.1 displays the results of this simulation. 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 failures change other banks' risk in the A matrix).

5 Network Features and Bank Survivorship

5.1 Predicting Bank Survivorship for the Entire Network

Because our underlying analysis is based on bank-level data, we can also analyze whether systemic risk measures improve model fit of subsequent banking distress. 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

[26]RFC assistance is not the same as the bank being "quarantined." Many banks failed despite receiving RFC assistance.

otherwise.[27] 62% of the sample survives and the remainder exits. In this section, we do not differentiate between failures and mergers; however, in Appendix Section A.5, we disentangle failures and mergers.

We consider two probit models, where in latent-variable form:

$$M_1: \quad y_i^* = x_{i1}^\top \cdot \beta_1 + \varepsilon_i \tag{11}$$

and

$$M_2: \quad y_i^* = x_{i1}^\top \cdot \beta_1 + x_{i2}^\top \cdot \beta_2 + \varepsilon_i. \tag{12}$$

For both, the mapping from the latent to the observed data is $y_i = 1\{y_i^* > 0\}$ and $\varepsilon_i \sim N(0,1)$. The covariates in the vector x_{i1} include a rich set of controls, including balance sheet data on bank i, its location, and information on local bank competition. We include additional county and state-level controls capturing differences in economic structure and financial regulation, much of which varied at the state level (Mitchener, 2005, 2007). Because we are interested in modeling the entire banking network and capturing the failures that occurred between 1929 and 1934, the majority of which were non-Fed member banks, we use the bank-specific data from Rand McNally as they are included in that publication.[28] These controls were selected following Calomiris and Mason (2003). Table 6 provides detailed descriptions of our control variables, which include measures for the size of the balance sheet, balance sheet ratios, the number of banks in the county, the share of deposits held at that bank as a ratio of total deposits in the county, Federal Reserve membership, indicators for whether the bank is located in a reserve city or central reserve city, county population, manufacturing establishments and acreage of cropland in the county, and Federal Reserve district indicators. Lastly, motivated by work showing the differences in bank outcomes in areas with and without branch banking, we include a measure for the intensity of branching in the bank's location (Carlson, 2004; Mitchener, 2005; Carlson and Mitchener, 2006). Fol-

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

[28] More detailed balance sheet information is available for the subset of Federal Reserve member banks, however, there is a clear tradeoff when it comes to modeling systemic risk: 73% of the exits from the system were nonmembers. The results for the entire commercial banking system seem more relevant since our goal is to test whether systemic risk measures improve model fit rather than, for example, trying to present causal estimates of bank failures. For a review of national banks, see Calomiris et al. (2019).

lowing Carlson and Mitchener (2006), the branching intensity variable is the share of banks operating branches in the state.

Table 6: Definitions of the variables that enter specifications M_1 and M_2.

Model	Variable	Definition
M_1, M_2	Loans/Deposits	Ratio of loans and discounts to deposits
M_1, M_2	Bonds/Assets	Ratio of bonds and securities to total assets
M_1, M_2	LnAssets	Ln(Total Assets)
M_2	EigenCent	Eigenvalue Centrality, C
M_2	Composite Risk	Composite Risk Score, R
M_2	SysRisk Percent	Percent contribution to systemic risk (S)
M_1, M_2	Fed Member	Indicator for Federal Reserve membership
M_1, M_2	Central Reserve City	Indicator for central reserve city location
M_1, M_2	Reserve City	Indicator for reserve city location
M_1, M_2	LnPopulation	Ln(County Population)
M_1, M_2	Manufact per capita	Manufacturing establishments in the county divided by county population†
M_1, M_2	Cropland per capita	Acreage of cropland in the county divided by county population
M_1, M_2	Branch Intensity	Ratio of number of banks operating branches in the state to total number of banks in the state
M_1, M_2	Num Banks in County	Number of banks operating in the county†
M_1, M_2	Deposits/County Deposits	Ratio of deposits held at the bank to the sum of all bank deposits in the county
M_2	Fed Mem $\times$ SysRisk Percent	Interaction between Federal Reserve membership and percent contribution to systemic risk
M_2	Branch $\times$ EigenCent	Interaction between Branch Intensity and Eigenvalue Centrality†

Note: County population, manufacturing establishments, and acres of cropland are from the 1930 *U.S. Census of Population, Manufacturing, and Agriculture*. †Manufact per capita is multiplied by 100 and Branch $\times$ EigenCent is multiplied by 10 to rescale for numerical precision. Num of Banks in County is divided by 10.

Our main variables of interest, measures for systemic risk for bank i in 1929, are in the vector x_{i2}, namely, composite risk score (R), eigenvalue centrality, and percent contribution to systemic risk. Additionally, we include two interaction terms that allow us to investigate how the institutional structure of the Federal Reserve System and the legalities that underlie branching systems modify the correspondent network's impact on bank survival. First, we interact Federal Reserve membership with the percent contribution to systemic risk since the experience of Federal Reserve member banks differed from nonmembers. They had access to discount lending facilities and the average sizes of their assets, connections, and market shares were much larger than nonmembers.[29] Second, we interact branching intensity with eigenvalue centrality. The tension that existed in the late 1920s between the correspondent network and branch banking is well-documented (Curtis, 1930; Nadler and Bogen, 1933). Many large correspondent banks took the lead in opposing branch banking as they were concerned that small banks would join a branching system instead of their correspondent business (Abrams and Settle, 1993).[30] This interaction term this allows us to examine how the presence of two different types of networks influenced survivability.

5.2 Estimation and Model Comparison

We first conduct a model comparison exercise to understand whether models including network-based systemic risk measures are useful for predicting subsequent banking distress. Because few existing studies have bank-level data on the full population of banks, model testing has received comparatively less attention in the empirical literature on systemic risk, despite its potential importance. We estimate the models using 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 (Greenberg, 2008). Because our primary goal in this section is to compare models with and without measures for bank-specific systemic risk, these features of the Bayesian approach allow us to understand how the data support these measures as predictors of bank survival. For Bayesian estimation, the Accept-Reject Metropolis-Hastings (ARMH) algorithm is used to fit the model (Tierney, 1994; Chib and Jeliazkov, 2001). The priors on β are centered at 0 with a standard deviation of 10 and the results are based on 10,000 MCMC draws with a burn in of 1,000.[31]

[29] The reason we selected percent contribution to systemic risk for the interaction is because this measure captures both the network and the balance sheet – two items that would be included in the Federal Reserve System's oversight.

[30] The reason we selected eigenvalue centrality for the interaction is because this measure only captures the correspondent network, without balance sheet effects.

[31] The parameter and marginal likelihood estimates are robust to various hyperparameters on the prior distributions, as well as using a training sample for the prior.

Marginal likelihoods ($\ln f(y|M_1)$ versus $\ln f(y|M_2)$) have several advantageous properties. They lead to finite sample model probabilities, do not require competing models to be nested, and provide a measure of *sequential out-of-sample predictive fit*, which makes better use of the data for model comparison. The latter of these is less well-known. Choudhary et al. (2017) show that for model M_l:

$$f(y|M_l) = \prod_{i=1}^{n} f\left(y_i | \{y_j\}_{j<i}, M_l\right) \tag{13}$$

$$= \prod_{i=1}^{n} \int f\left(y_i | \{y_j\}_{j<i}, \beta_l, M_l\right) \pi\left(\beta_l | \{y_j\}_{j<i}, M_l\right) d\beta_l. \tag{14}$$

Equation 13 represents the marginal likelihood as the product of n one-step-ahead sequential predictive densities, which follows from the law of total probability. Equation 14 then shows that these n one-step-ahead sequential predictive densities correspond to the cumulative out-of-sample prediction, where the fit of observation i is measured with respect to the posterior density, $\pi(\beta|y)$, based only on data up to the ith observation (not conditioning on anything after i, $\{y_j\}_{j\geq i}$). In-sample measures condition on the entire dataset, whereas other out-of-sample measures typically require the researcher to use a subset of the data for estimation and the remainder for prediction. Thus, the results depend on which data were used for estimation. Marginal likelihoods, on the other hand, are invariant to rearranging the data. Given that we are using ARMH, following Chib and Jeliazkov (2001), we can use the building blocks of that algorithm to compute marginal likelihoods.

Table 7 presents the marginal likelihood estimates and shows strong evidence in favor of M_2. In particular, the specification has a posterior model probability of nearly 1 in comparison with M_1. Given that M_1 and M_2 represent competing hypotheses about whether network measures are important for modeling bank survival, we show the odds in favor of M_2 over M_1 are high, meaning the data are more likely to occur under M_2.[32] The data support the specification with the additional measures (*EigenCent*, *Composite Risk*, *SysRisk Percent*, and the two interactions) in predicting the probability of bank survival, as M_2 dominates M_1.

While the marginal likelihood is the superior measure for sequential out-of-sample pre-

[32]The odds in favor of network measures over no network predictors is $\approx 1.07 \times 10^{156} : 1$. The chi-square test for confusion matrix differences between M_1 and M_2 is also highly significant with a p-value of zero.

Table 7: Model Comparison Results for M_1 and M_2.

	M_1	M_2
Log-Marginal Likelihood	-15345.24	-14985.97
Numerical Standard Error	(0.008)	(0.020)
Posterior Model Probability	9.35×10^{-157}	≈ 1

dictive fit, the in-sample classification rates give us straightforward and intuitive numbers. With the inclusion of network, composite risk, and interaction variables, outcomes for over 300 additional banks are correctly classified. Overall, these new variables constructed from bank correspondent networks have significant explanatory power when it comes to specifying the probability of bank survival during the Depression.

5.3 Bank Survivorship during the Great Depression

Having demonstrated that the data strongly support models including bank-specific systemic risk measures, we now turn our attention to examining how the different elements of the network affected bank survivability during the Great Depression. The discussion of the parameter estimates focuses on M_2 since it is a superior model. We begin with a brief discussion of the coefficients on our control variables, comparing them to results from other studies on the Great Depression. Table 8 shows that bank size (measured by LnAssets) and the ratio of Bonds/Assets are positively associated with bank survival. The Loans/Deposits ratio and the number of banks in the county, a measure of local competition, have a negative impact on bank survival. The market share of the bank (measured by the share of county deposits held at that bank) has a positive impact, consistent with Calomiris and Mason (2003). Lower probabilities of survivorship are associated with the indicator variables for central reserve city and reserve city. These results align 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 banks located in the hinterland.

We now turn our attention to examining the coefficients on network features, systemic risk, and interaction terms, our novel contribution to the literature on the Great Depression.

Table 8: Modeling bank survivorship. Posterior means and standard deviations (in parentheses) are presented for M_1 and M_2. Maximum likelihood estimates and standard errors are presented in Appendix Table A.4.1.

	M_1	M_2
Intercept	-0.988 (0.175)	0.095 (0.183)
Loans/Deposits	-0.023 (0.045)	-0.303 (0.048)
Bonds/Assets	1.086 (0.073)	0.731 (0.075)
LnAssets	0.187 (0.009)	0.148 (0.010)
EigenCent		3.041 (1.615)
Composite Risk		-0.060 (0.000)
SysRisk Percent		-7.138 (2.921)
Fed Member	0.025 (0.019)	0.029 (0.021)
Fed Member × SysRisk Percent		7.995 (2.892)
Branch Intensity	0.740 (0.211)	1.109 (0.241)
Branch Intensity × EigenCent		-5.105 (2.161)
Num Banks in County	-0.004 (0.004)	-0.008 (0.004)
Deposits/County Deposits	0.339 (0.066)	0.393 (0.068)
Central Reserve City	-1.078 (0.102)	-1.050 (0.103)
Reserve City	-0.359 (0.042)	-0.317 (0.043)
LnPopulation	-0.101 (0.014)	-0.088 (0.014)
Manufact per capita	0.480 (0.105)	0.554 (0.105)
Cropland per capita	-0.003 (0.000)	-0.003 (0.001)
Fed. Dist. FE	Yes	Yes
n	24,761	24,761

As shown in M_2, all of these variables and their interactions are statistically different from 0 (based on a 90% credibility interval). The new measures employed in this paper 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. Other systemic risk measures, such as CoVAR, are developed from regression output. Thus, using such measures as covariates in an empirical setting based on micro data such as ours would lead to generated regressor issues and require standard-error adjustments. Here, we can simply include these measures as covariates and move forward with interpretation.

Composite risk score is negatively-signed, which is quite intuitive and aligns with results found in numerous studies on bank survivability. Eigenvalue centrality, measuring the importance of a bank's position in the network, is positive whereas a bank's contribution to systemic risk is negative. Thus, during the Great Depression, a prominent network position raised a bank's predicted survivability unless the bank also had a risky balance sheet, in which case it lowered the bank's probability of surviving the distress of the 1930s. The positively-signed coefficient on the interaction between Federal Reserve membership and systemic risk contribution sheds additional light on these results: being a Fed-member bank offsets the negative impact on survivability coming from systemic risk contribution. Further, the Federal Reserve membership indicator is not statistically different from zero. Hence, as it pertains to the interbank network, the experience of Federal Reserve members was drastically different than that of nonmembers.

To understand the magnitude of these differences, we compute the marginal effect of systemic risk contribution on the probability of bank survival for members and nonmembers. Following Jeliazkov and Vossmeyer (2018), computation of the covariate effect is done by marginalizing over the parameters with the posterior distribution and marginalizing over the sample with the empirical distribution of the covariates:

$$\delta_{SysRisk} = \int \frac{\partial \Pr\left(y_i = 1|x, \beta\right)}{\partial x_{SysRisk}} f\left(x\right) \pi\left(\beta|y\right) dx d\beta. \tag{15}$$

We find that the marginal effect of a Fed member bank's contribution to systemic risk is 0.272 and the marginal effect of a nonmember bank's contribution to systemic risk is -2.524. The distributions of these average effects as a function of parameter uncertainty and units in the sample are presented in Figure 6.

Thus, on average and all else equal, a marginal increase in systemic risk increases the probability of survival for Fed-members by 0.27%. On the other hand, a marginal increase in systemic risk for nonmembers decreases the probability of survival by 2.52%. There are several possible explanations for these dramatically different outcomes in survivability. First, Federal Reserve members had access to the Discount Window (DW), and while it is documented that certain Federal Reserve regional banks could have done more to mitigate panics (Friedman and Schwartz, 1963; Richardson and Troost, 2009), a sizable amount of credit was dispersed by the Federal Reserve (Wheelock, 2010) to member banks and perhaps

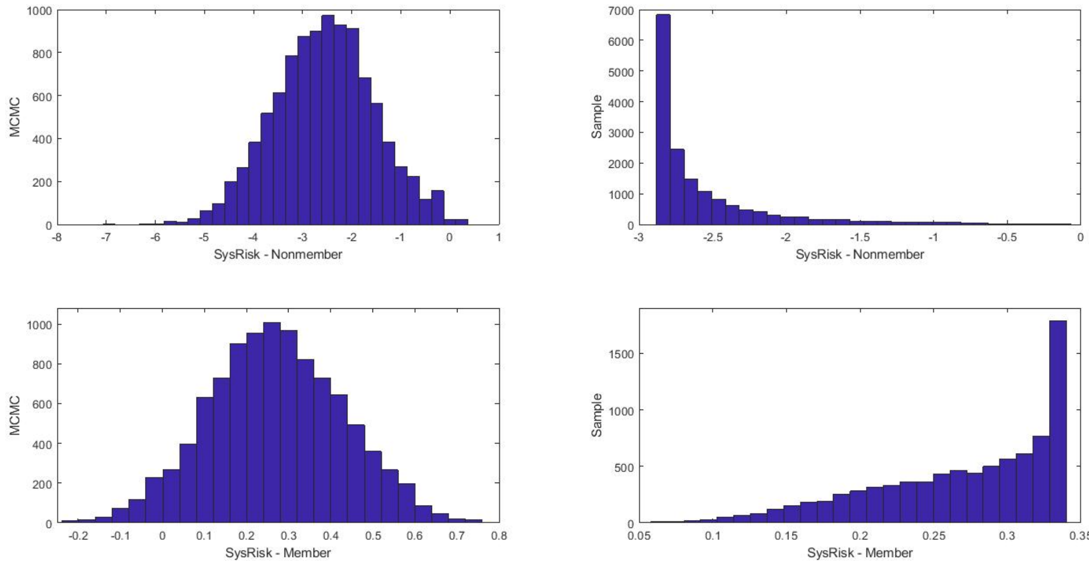

Figure 6: Marginal effects of systemic risk contribution for nonmembers (top) and members (bottom). Distributions of the average effect as a function of parameter uncertainty is on the left side and as a function of units in the sample is on the right side.

thereafter onto connected member banks.[33] Second, all of the top systemic risk contributors in Table 4 were Federal Reserve members and over 70% of these banks received large injections from the Reconstruction Finance Corporation's (RFC) 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).[34] If we allow for the possibility that both of these mechanisms were operating, and given that, of the top 200 systemic risk contributors, only 10 were nonmembers (the survivorship rate for members in the top 200 was 75%, whereas it was 50% for nonmembers), it seems reasonable to conclude that this episode in financial history points to too-big-to-fail policies being applied

[33]There was considerable disagreement within the system about aiding nonmember banks, including concerns about free riding by nonmembers (not contributing to upkeep or being subject to examination) as well as whether paper presented as collateral was eligible for rediscounting – debates that were not resolved until after the banking crises had subsided (Richardson and Troost, 2009).

[34]Note that the RFC application and examiner files do not report or comment on the bank's correspondent network. Only in the case of large institutions, such as Continental Illinois, does Jesse Jones mention the network. He states that Continental was a "good correspondent" (Jones, 1951). Otherwise, for typical RFC applicants, network information was not readily accessible on the required paperwork (Vossmeyer, 2016). Calomiris et al. (2013) provide additional information on the RFC and the correspondent network.

to well-connected Federal Reserve member banks. Policies designed to rescue banks that were very interconnected in the correspondent network system is also noted in Gorton and Tallman (2018). Appendix Figure A.2.1 shows that most exits from the network were small to medium-sized banks.

As shown in Table 8, the branching intensity effect is positive, which is consistent with Mitchener (2005, 2007), who finds that laws prohibiting branching raised suspension rates for banks. Interestingly, the interaction between branch intensity and eigenvalue centrality is negative, offsetting some of the positive effect from eigenvalue centrality. To understand the magnitude of and differences in eigenvalue centrality's impact on bank survival in branching and non-branching areas, we compute covariate effects as in equation 15. The derivative is taken with respect to $x_{eigencent}$, and this effect is computed for the subsample of banks operating in areas with branching (Branching Intensity $\neq 0$) and for the subsample of banks located in areas with no branching (Branching Intensity $= 0$).

We find that the marginal effect of eigenvalue centrality in branching areas is 0.863 and the marginal effect of eigenvalue centrality in non-branching areas is 1.051, 22% higher. The distributions of these average effects as a function of parameter uncertainty and units in the sample are presented in Figure 7. Thus, as the intensity of branch banking in an area increases, the value of eigenvalue centrality and the correspondent network, in general, decreases. This result aligns with the understanding of the tension between the correspondent network and branching. Large banks that opposed branching thought that, if branching were allowed, small country banks would join the branching system, as opposed to seeking services from correspondents. Thus, many large correspondents believed branch banking would "jeopardize their profitable correspondent business" (Abrams and Settle, 1993). (Curtis, 1930, p. 179) states:

> The development of branch banking will also tend to disrupt the present relationship of city and country bank correspondents. Certain metropolitan banks will lose correspondents and business unless they, too, establish branches. But the relationship of parent and branch will be much more direct and intimate and dependable than that of correspondents and, therefore, the seasonal and panic

demands for funds will be better cared for, and an economy will be realized because it will no longer be necessary to carry balances with correspondents.

Indeed, the sign of the interaction provides statistical evidence of these competing network forces. We show the effectiveness of the interbank network for bank survival diminishes in areas where branching exists. Banks in branching areas had a higher probability of bank survival, attributing more benefits to the branching system.

The results for the two interaction variables are large, statistically different from zero, and have important general implications. The impact of the correspondent network is not uniform and changes as one conditions on institutional structures and regulatory frameworks. The experience of the Great Depression demonstrates this point using spatial variation in Federal Reserve membership and branching laws.

Next, we consider two counterfactual scenarios: (i) how the probability of bank survivorship would change if all commercial banks had joined the Federal Reserve System prior to

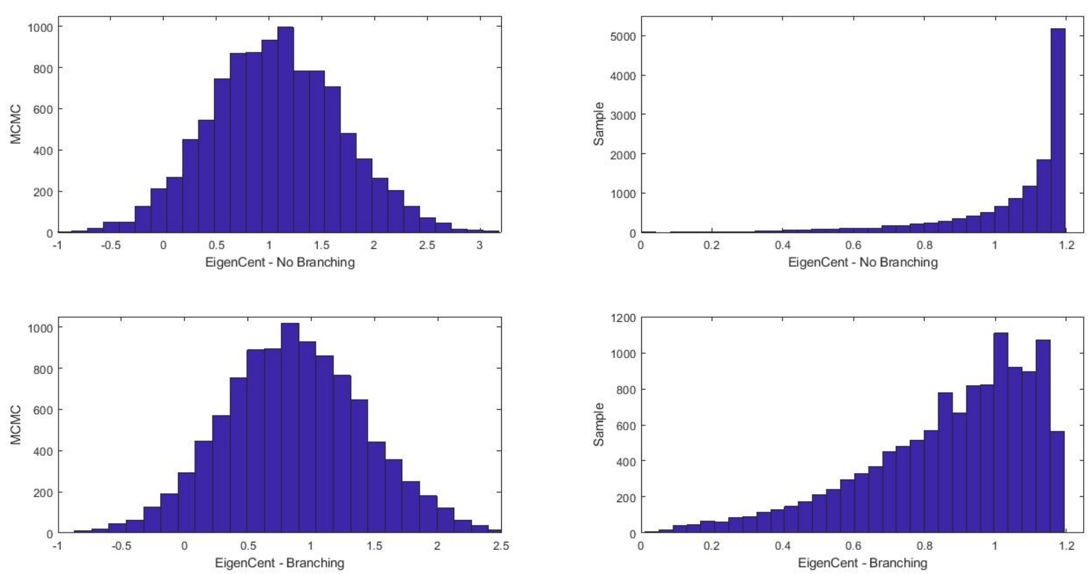

Figure 7: Marginal effects of eigenvalue centrality for non-branching areas (top) and branching areas (bottom). Distributions of the average effect as a function of parameter uncertainty is on the left side and as a function of units in the sample is on the right side.

the start of the Depression and (ii) how the probability of bank survivorship would change if the network had a random topology instead of a pyramid shape. The quantity we seek, δ_{cf}, is the expected difference in computed pointwise probabilities as $x_i^{\dagger}$ (the original case) is changed to $x_i^{\ddagger}$ (the counterfactual case):

$$\delta_{cf} = \int [\Pr\left(y_i = 1 | x^{\dagger}, \beta\right) - \Pr\left(y_i = 1 | x^{\ddagger}, \beta\right)] f(x) \, \pi(\beta | y) \, dx d\beta. \tag{16}$$

For the Federal Reserve membership counterfactual, we take the sample of banks that were not members ($n = 16,337$) and generate an alternative covariate matrix $x_{fed}^{\ddagger}$ where the indicators associated with Fed membership now equal 1. We find that the difference in the probability of bank survival is -0.017. Thus, if nonmembers were granted Fed membership, their probability of bank survival is 1.7 percentage points higher than when they were nonmembers. Figure 8 presents the distribution of this average effect as a function of parameter uncertainty, which shows that it is statistically different from 0. Additionally, this probability difference is computed holding all else fixed, so bank size, balance sheet, network position, and location all remain constant. 1.7 percentage points translates to 278 additional bank survivals. Universal Federal Reserve membership would have made a positive impact on bank survival.

For the random network counterfactual, as in Section 3.2, we generate random networks with the same number of nodes and the same mean degree as the 1929 network, resulting in a new network adjacency matrix, A_{rn}. A_{rn} is then used to create new variables for eigenvector centrality and systemic risk contribution. The vector R in the computation of systemic risk remains the same, only the adjacency matrix is changing. We generate 100 different random networks and average the variables across them, so the results are not specific to a particular realization.[35] With these new variables, we create a counterfactual covariate matrix $x_{rn}^{\ddagger}$, where eigenvector centrality and systemic risk contribution are computed from random networks, and the effects of central reserve city and reserve city are removed. All of the other variables (balance sheet size, ratios, location, etc.) remain the same. The covariate matrix $x_{rn}^{\ddagger}$ represents the scenario where the pyramid-shape of the correspondent network no longer exists and the network is flattened.

[35]The expected value of eigenvector centrality equals $\frac{1}{\sqrt{n}}$.

We find that the difference in the probability of bank survival is -0.0103. Thus, if the correspondent network had a random topology, the probability of bank survival is 1.03 percentage points higher than when the topology is pyramid-shaped. Figure 8 presents the distribution of this average effect as a function of parameter uncertainty, which shows that it is statistically different from 0. This difference translates to roughly 255 additional bank survivals. While the parameter estimates show that subsets of banks benefitted from the network and others were harmed by it, here we show that on average, the pyramid network did more harm than good for bank survival during the Great Depression. This result aligns with Acemoglu et al. (2015), who show that in times of large negative shocks, dense network structures can be a source of economic instability.

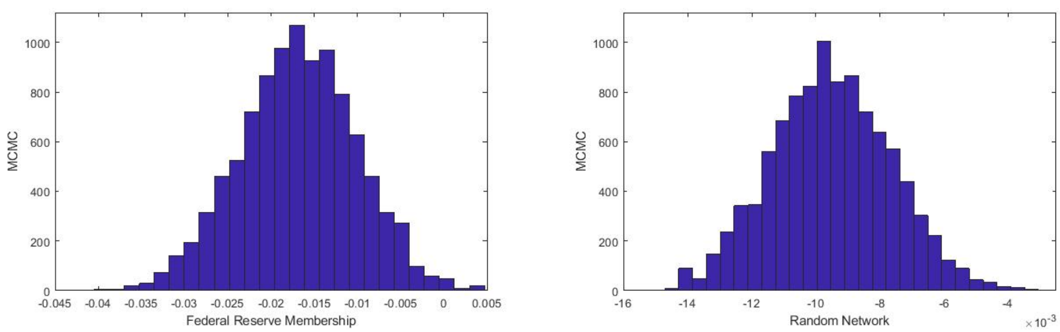

Figure 8: Covariate effects of Federal Reserve membership (left) and random network topology (right). The distributions are of the average effect as a function of parameter uncertainty.

Robustness checks, maximum likelihood estimates (with standard error adjustments), OLS estimates, and information criteria for the probit specification are provided in Appendix A.4. We additionally show in the appendix that the estimated coefficients are robust to including state fixed effects; however, the fixed effects lead to overfitting as the information criteria do not favor the specification. Therefore, the results presented in this main body are the strongest, and most supported by the data. Furthermore, Appendix A.5 presents an ordered specification in which we disentangle mergers and failures from the "exit" group. In the 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. The results for the ordered specification on the subsample of national banks align with the binary specification and show significant support in favor of a model that includes our bank-specific systemic risk measures to predict the probability of bank survival, merger, and failure.

6 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 crisis of the 20th century altered banking network properties and the concentration of risk. We combine interconnectedness and credit quality of financial institutions in the system to produce a single measure of systemic risk, which is decomposable into individual bank contributions. We find that the resulting failure of over 9,000 banks increased systemic risk by 33%, a result that is both quantitatively and statistically significant. Further, the banking crises of the early 1930s caused risk to become more concentrated, with the 20 systemically-riskiest banks increasing their contribution to systemic risk by 5 percentage points between 1929 and 1934.

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, relative to “random graph” and “bootstrapped scale-free” topologies, and increased the incidence of failures by 255 banks. This finding of the network’s pyramid-shaped topology in 1929 – a relic from the pre-Fed era that had become “locked in” through state regulation of nonmember banks – is a potentially important finding for policymakers. It highlights an additional dimension on which systemic risk scoring should be analyzed, and it underscores the self-reinforcing nature of networks, showing that “history can matter” when there is the possibility of lock-in at a Pareto inferior equilibrium (Arthur, 1988, 1989; Farrell and Shapiro, 1989; Gallini and Karp, 1989; Klemperer, 1987a,b; Beggs and Klemperer, 1992).

The results from our micro-analysis of the Great Depression suggest that, in modeling the probability of bank survival, network position and systemic risk are key to the specification and greatly improve the model’s sequential out-of-sample predictive fit. The analysis shows that banks with higher ex ante default risk in 1929 were more likely to subsequently fail. And, unlike the Great Recession, financial distress tended to be concentrated in small and medium-sized banks. For most banks in the system, systemic risk led to a higher probability of bank failure. However, Federal Reserve members do not seem to experience these same negative effects – a particularly interesting result in light of the actions taken by the Reconstruction Finance Corporation (RFC) and recent policy discussions surrounding too-connected-to-fail banks. Indeed, had all commercial banks become Fed members prior to the start of the Depression, all else equal, we estimate this institutional change would have resulted in at least 278 fewer bank failures. We also show that in areas where branch banking was intense, the effectiveness of the correspondent network was weaker, demonstrating how the presence of two different types of networks influenced survivability. Unfolding these differing locational and institutional systemic risk and network results is only possible by studying the Great Depression because current Federal Reserve policy and banking regulations are much more uniform across the United States.

Our research reinforces another point emerging from recent work on the GFC: large macro shocks may have different effects on the financial system depending on the structure of network connections. Brunetti et al. (2019) analyze the interbank market around 2008 and find that physical or stated network connectivity provides meaningful forecasts of subsequent liquidity problems. Our analysis of the Great Depression, which also uses stated relationships to examine bank survivorship, complements these findings. During the banking panics of the 1930s, demand for liquidity soared. Smaller and medium-sized banks, which were unable to procure liquidity, often failed. The uniqueness of the network topology during the Great Depression and the vast 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 and antecedents 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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A Appendix

A.1 R as a Measure of Risk

Credit ratings are typically employed as the measure for internal balance sheet risk. However, this is not available for our sample, leading us to make use of the eight asset and liability categories we have from each bank's balance sheet. As a result, we develop the measure R which is the product of transformed leverage and inverse profitability risk score. To understand how well R captures risk, we compare R to several standard balance sheet measures that are often employed in banking studies. We mimic the balance sheet measures used in Calomiris and Mason (2003). However, since we are studying all banks, instead of limiting the sample to Federal Reserve members, we are unable to replicate all of the measures used in that study as our balance sheet categories are not as granular. For comparison, we look at how well each measure fits a probit model bank survival. The outcome variable for the probit model equals 1 if the bank appears in 1934 and 0 otherwise.

Table A.1.1 presents the estimate of each risk measure, and the log-marginal likelihood estimate and BIC of a model with only the tested risk measure and an intercept. The composite risk score R has the highest marginal likelihood and lowest BIC, thus providing evidence that the data support this as a measure of risk, relative to the 7 other measures tested.

Table A.1.1: The log-marginal likelihood estimate and BIC associated with each model where only an intercept and the risk measure are used as covariates in a probit model of bank survival.

Model and Risk Measure	Estimate	MargLik	BIC
1. Composite Risk, R	**-0.073 (0.002)**	**-15807.93**	**31588**
2. Loans/Deposits Ratio	-0.610 (0.029)	-16360.28	32715
3. Non-Cash Assets/Total Assets Ratio	-1.341 (0.043)	-16144.65	32268
4. Loans/Total Assets Ratio	-0.927 (0.044)	-16350.35	32696
5. Bonds/Total Assets Ratio	1.442 (0.044)	-16091.55	32162
6. ROA, Surplus & Profits /Total Assets	5.801 (0.163)	-16155.61	32268
7. Total Assets/Equity	0.009 (0.002)	-16520.83	33030
8. ln(1+Total Assets/Equity)	0.144 (0.019)	-16506.97	33007

A.2 Bank Exits

Between 1929 and 1934, the number of nodes in the network decreased by 36%. 9,238 banks exited the network, which is largely attributable to failures and mergers. Figure A.2.1 presents a histogram of all bank exits as a function of (log) total assets in 1929. For comparison purposes, the 25th, 50th, and 75th percentiles of the asset distribution for all banks (not just exits) are displayed by the red dashed lines. Clearly, most of the banks that exited the network were smaller than the median-sized bank in the system.

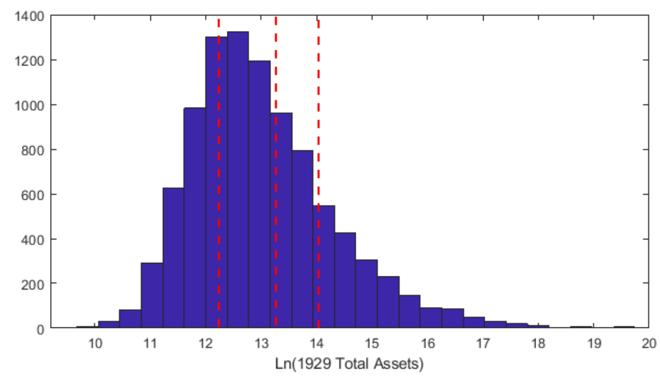

Figure A.2.1: Histogram of bank exits from the network by 1934 as a function of (log) total assets in 1929. The red dashed lines represent the 25th, 50th, and 75th percentiles of the asset distribution of the entire banking population (not just exits) in 1929.

A.3 Counterfactuals

Table A.3.1 displays the simulation results for the hypothetical failure of the 10 systemically riskiest banks in 1929. The simultaneous failure of all 10 would raise systemic risk by over 50%.

Table A.3.1: 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

A.4 Robustness

Table A.4.1 shows the robustness of our results to additional specifications and estimation methods. We present the maximum likelihood results for M_1 and M_2 when y is binary, which align closely with the posterior means. Additionally, we report the information criteria associated with each model. The model rankings from the information criteria are the same as the marginal likelihood rankings. Column M_2-S.E. reports the MLE results with robust standard errors clustered at the county level, which do not change the statistical significance of our parameter estimates.

The columns M_3 and M_4 report the results for both models with state fixed effects. The main results are preserved, but the information criteria suggest overfitting. Therefore, we focus our analysis on M_2. While omitted variables are always a concern in large-scale analyses, the overfitting that stems from the models with state fixed effects suggests that our balance sheet, correspondent network, county, and Federal Reserve measures are comprehensive at explaining bank survival, outside of state geography. Lastly, M_1-OLS and M_2-OLS report the results for both models when estimation is done by OLS.

Table A.4.1: Maximum likelihood estimates and standard errors are presented for M_1 and M_2 (full sample). Column M_2-S.E reports the MLE results with robust standard errors clustered at the county level. Columns M_3 and M_4 report the results for both models with state fixed effects. Columns M_1-OLS and M_2-OLS report the results for both models when estimation is done by OLS. *** implies significance at the 1% level, ** implies significance at the 5% level, * implies significance at the 10% level.

	M_1-MLE	M_2-MLE	M_2-S.E.	M_3	M_4	M_1-OLS	M_2-OLS
Intercept	-0.997 (0.187)***	0.079 (0.200)	(0.281)	-0.232 (0.396)	-1.583 (0.385)***	0.116 (0.064)	0.496 (0.067)***
Loans/Deposits	-0.022 (0.048)	-0.304 (0.050)***	(0.053)***	-0.349 (0.051)***	-0.106 (0.050)**	-0.011 (0.017)	-0.111 (0.018)***
Bonds/Assets	1.085 (0.078)***	0.728 (0.080)***	(0.089)***	0.661 (0.083)***	0.989 (0.081)***	0.369 (0.027)***	0.226 (0.027)***
LnAssets	0.187 (0.010)***	0.148 (0.011)***	(0.012)***	0.148 (0.011)***	0.193 (0.010)***	0.066 (0.003)***	0.051 (0.004)***
EigenCent		3.243 (1.886)*	(1.901)*	4.826 (1.949)**			0.745 (0.553)
Composite Risk		-0.060 (0.002)***	(0.002)***	-0.059 (0.002)***			-0.021 (0.001)***
SysRisk Percent		-8.687 (3.513)**	(4.179)**	-7.264 (3.556)**			-3.087 (1.277)**
Fed Member	0.025 (0.020)	0.025 (0.022)	(0.027)	0.032 (0.022)	0.030 (0.020)	0.013 (.007)*	0.016 (0.007)**
Fed Member × SysRisk Percent		9.482 (3.487)***	(4.211)**	7.844 (3.530)**			3.163 (1.266)***
Branch Intensity	0.738 (0.223)***	1.120 (0.258)***	(0.312)***	12.388 (5.578)**	15.080 (5.506)***	0.231 (0.075)***	0.307 (0.081)***
Branch Intensity × EigenCent		-5.467 (2.321)**	(2.317)**	-5.018 (2.495)**			-1.109 (0.625)*
Num Banks in County	-0.004 (0.003)	-0.009 (0.004)**	(0.004)**	-0.004 (0.004)	-0.003 (0.004)	-0.001 (0.001)	-0.003 (0.001)**
Deposits/County Deposits	0.338 (0.070)***	0.392 (0.071)***	(0.079)***	0.429 (0.075)***	0.374 (0.073)***	0.114 (0.024)***	-0.129 (0.024)
Central Reserve City	-1.075 (0.108)***	-1.045 (0.111)***	(0.169)***	-0.915 (0.115)***	-0.950 (0.113)***	-0.360 (0.036)***	-0.333 (0.036)***
Reserve City	-0.360 (0.045)***	-0.316 (0.046)***	(0.070)***	-0.327 (0.048)***	-0.374 (0.047)***	-0.128 (0.016)***	-0.110 (0.016)***
LnPopulation	-0.100 (0.014)***	-0.088 (0.015)***	(0.021)***	-0.087 (0.016)***	-0.101 (0.015)***	-0.035 (0.005)***	-0.030 (0.005)***
Manufact per capita	0.475 (0.111)***	0.555 (0.113)***	(0.169)***	0.130 (0.126)	0.080 (0.123)	0.166 (0.039)***	0.187 (0.038)***
Cropland per capita	-0.003 (0.001)***	-0.003 (0.001)**	(0.001)**	-0.001 (0.001)	-0.002 (0.001)	-0.001 (0.000)***	-0.001 (0.000)***
Fed. Dist. FE	Yes	Yes		Yes	Yes	Yes	Yes
State FE	No	No		Yes	Yes	No	No
n	24,761	24,761		24,761	24,761	24,761	24,761
BIC	30652.33	29951.38		30082.79	30730.57	32293.58	31597.72

A.5 Ordered Specification

To obtain results for the population of commercial banks, our outcome variable combined failures and mergers, but these outcomes clearly differ. We lack detailed information on survival outcomes of state banks; however, for national banks, we are able to further distinguish between these types of exits using data from the *Annual Report* of the Comptroller of the Currency (1929-1934). All national banks are, by definition, members of the Federal Reserve System, and based on the full-sample results above, we know there are differences among Fed and non-Fed members; hence, the smaller sample is not representative. The sample of national banks is nevertheless useful for testing the robustness of our model comparison results.

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

$$y_i = \begin{cases} 3 \quad \text{Bank Survives} \quad \gamma_3 > y_i^* \leq \gamma_2 \\ 2 \quad \text{Bank Merges} \quad \gamma_2 > y_i^* \leq \gamma_1 \\ 1 \quad \text{Bank Fails} \quad \gamma_1 > y_i^* \leq \gamma_0, \end{cases} \tag{17}$$

and $\varepsilon \sim N(0,1)$, i.e., an ordered probit model. 18% of the sample fail, 14% merge, and 68% survive. The models are estimated by Gibbs sampling methods (Algorithm 2 in Jeliazkov et al. (2008)), and the MLE parameter estimates align. The priors on β are centered at 0 with a standard deviation of 10 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 A.5.1: Model comparison results for the two ordered models.

	M_1	M_2
n	7,525	7,525
Log-Marginal Likelihood	-7499.95	-7264.49
Posterior Model Probability	5.51×10^{-103}	≈ 1

Table A.5.1 shows the model comparison results for the ordered probit models. As was true for the full population of commercial banks, a comparison of marginal likelihood reveals strong support for M_2, with a posterior model probability of nearly 1. These results align with the main findings in the paper 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.