

# Systemic Risk and the Great Depression

Sanjiv R. Das  
Department of Finance  
Santa Clara University

Kris James Mitchener  
Department of Economics  
Santa Clara University  
CAGE, CESifo, CEPR & NBER

Angela Vossmeier  
Robert Day School of Economics and Finance  
Claremont McKenna College\*

2019

## 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. The pyramid-like network topology increased the system's fragility and risk-spreading propensity. Systemic risk increased (decreased) the probability of bank survival for Federal Reserve members (nonmembers), and branch-banking dampened the positive effect on survival stemming from a bank's central position in the network.

*JEL classification:* L1, E42, E44, G01, G18, G21, N12, N22.

*Keywords:* Systemic risk; banking networks; Great Depression; Global Financial Crisis.

---

\*We are grateful to Charles Calomiris, Mark Carlson, Gary Gorton, Taylor Jaworski, Ivan Jeliazkov, Christoffer Koch, and conference and seminar participants at the NBER Summer Institute, Federal Reserve Bank of Dallas, Federal Reserve Bank of Atlanta, Bank of England, Federal Reserve Board, and Mountain West Economic History Conference for helpful comments and suggestions. We thank Jack Brown, Kendall Greenberg, and Peter Welch of the Lowe Institute of Political Economy, and Bhavika Booragadda, Lorraine Zhao, Tanisha Seth, Krystal Sung, Laira Aggarwal, and Hunter Olsen of the Financial Economics Institute for excellent research assistance. The authors may be reached at [srdas@scu.edu](mailto:srdas@scu.edu); [kmitchener@scu.edu](mailto:kmitchener@scu.edu); and [angela.vossmeier@cmc.edu](mailto:angela.vossmeier@cmc.edu).

# 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.<sup>1</sup>

In response, researchers have developed new analytical measures aimed at quantifying institutional as well as aggregate risk.<sup>2</sup> 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<sup>th</sup> 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 recent crisis. 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

---

<sup>1</sup>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).

<sup>2</sup>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 to test, more generally, whether the inclusion of network-based systemic risk measures improves model prediction.

We find that the massive banking crisis of the early 1930s reshaped the network and redistributed risk: it raised systemic risk per bank by 33% and increased the contribution of risk 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. We show that the pyramid-like structure of the commercial banking system that had evolved well prior to the Depression but was still in existence at its start had important consequences for systemic risk. Relative to “random graph” and “bootstrapped scale-free” topologies, the 1929 bank network topology exhibited higher fragility and propensity for risk to spread by concentrating banking interactions at particular nodes in the network. Had the 20 systemically riskiest banks failed, systemwide risk would have risen by over 50%. Only one of these banks, however, actually failed, raising overall systemic risk per bank by a mere 1.59%. Instead, bank failures in the early 1930s were largely concentrated in smaller- and medium-sized institutions – banks that, on average, had higher credit risk than larger institutions.

Using rich micro level data on individual banks, we also analyze how bank-specific in-

formation, 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. In addition, 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 were able to obtain 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 ([Jones, 1951](#)), which in the early 1930s, translated into well-connected Federal Reserve member banks. 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 2007-8 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 – an important finding for policymakers. Clearly, graph-theoretic models would have been useful in 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 how the system changed as a result of the banking crisis of 1930-33.<sup>3</sup> 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 Continen-

---

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

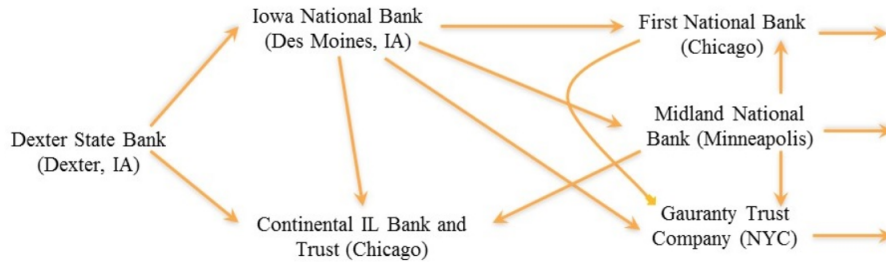


Figure 1: Illustrating correspondent relationships.

tal 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 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  $A(i, j)$ ,  $i, j = 1, 2, \dots, n$ , 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,  $A$

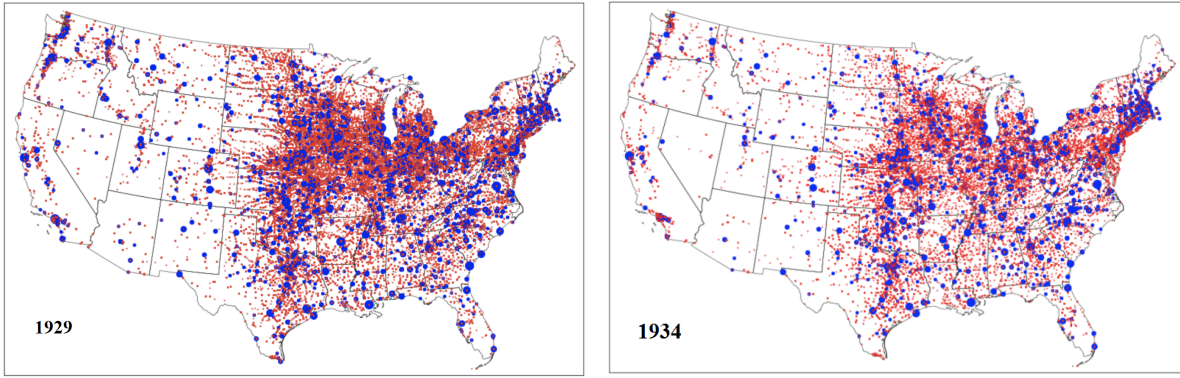


Figure 2: Respondent banks in red and correspondent banks in blue, sized by relative degree of each bank for 1929 and 1934. Respondent banks place money with correspondent banks. Correspondent banks are plotted in blue and have points that are two times 1 plus the natural logarithm of the node’s degree.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

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 1930–1933 irrevocably altered the US financial system.<sup>4</sup> 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 respondent banks declined by 36% (from 25,144 to 16,126) while the number of correspondents fell by 41% (from 3,602 to 2,134). The number of banks in

<sup>4</sup>For example, see [Friedman and Schwartz \(1963\)](#) and [Wicker \(1996\)](#).



the network declined by 36%, from 25,684 in 1929 to 16,446 in 1934, and the total number of links in the network fell by 41%, from 70,583 in 1929 to 41,313.

## 3.1 Network Statistics

### 3.1.1 Clusters, Degree, and Power Laws

To better understand the structure of the commercial bank network for the pre- and post-crisis years, we compute a variety of common network statistics. We first examine the density of the network. Clusters, defined here as the number of disjoint connected components, describe one aspect of network connectivity. In 1929, there were 31 such disjoint groups. Of these, there is one extremely large connected component of 25,576 banks (out of a total of 25,684). Therefore, the banking network 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.

The number of links that a node has is known as its degree, and the computation of degree is directionless. That is, even though our network is directed, degree only depends on a node's links, regardless of the directional linkage (i.e., respondent to correspondent or correspondent to respondent). For 1929, the mean degree of nodes in the network is 5.50 with a standard deviation of 49.60.<sup>5</sup> The median degree in the network is 3.0.

The “degree distribution” of the nodes is shown in Figure 3 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.<sup>6</sup> 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 4 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,

---

<sup>5</sup>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.

<sup>6</sup>This is characteristic of a scale-free network. For a full exposition, see <http://barabasi.com/f/623.pdf>. See also Barabasi and Bonabeau (2003).

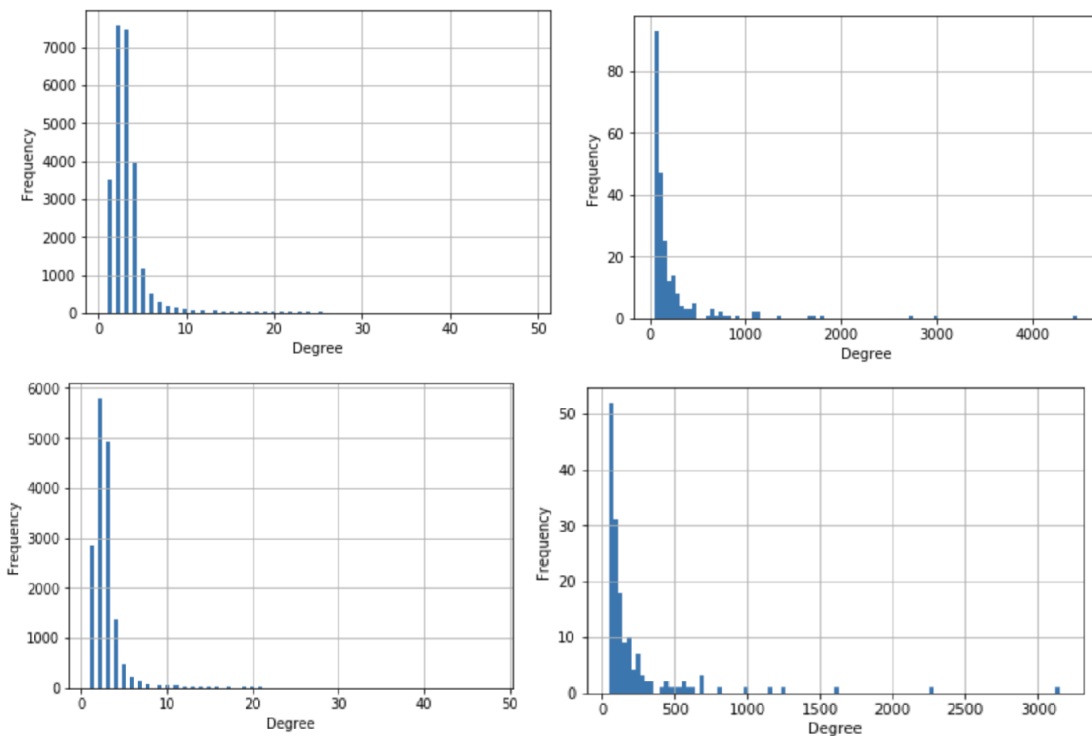


Figure 3: Degree distribution in 1929 (upper plots) and 1934 (lower plots). The left panels plot nodes with degree less than 50 while the right panels plot nodes with degree greater than 50.

2002; Barabasi and Bonabeau, 2003; Gabaix et al., 2003). Further, the node distribution can be compared to the size distribution of banks in 1929. The right panel of Figure 4 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 (reflecting the disappearance of many smaller banks from the system), the frequency plots of the degree of nodes for 1929 and 1934 look quite similar: the 1934 system still exhibits the usual power law distribution  $\alpha = 1.60$ . We also examined whether the network was different in 1934 versus 1929, by comparing the degree distributions in both years using

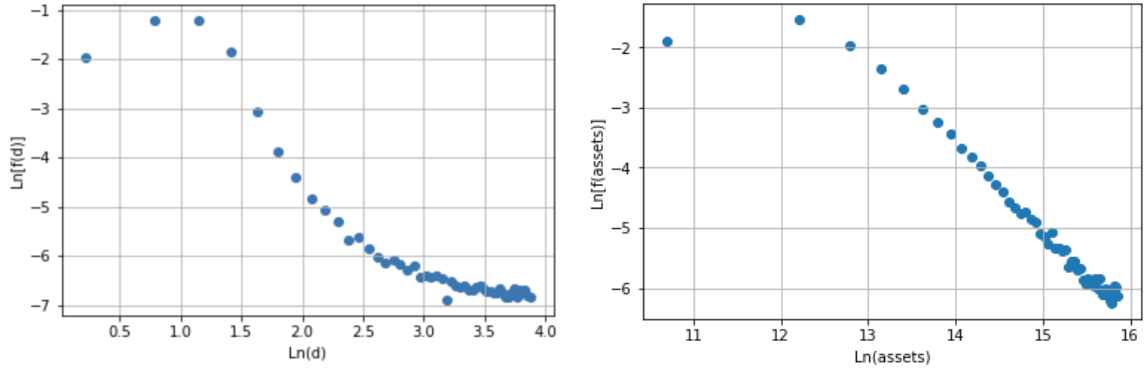


Figure 4: Network Density and Assets. Log-log plot of the degree distribution in 1929 excluding extreme nodes with degree greater than 50. We plot log degree on the x-axis and log of the density function on the y-axis. For power-law densities, the function is  $f(d) = d^{-\alpha}$ . Taking logs we have  $\ln[f(d)] = -\alpha \ln(d)$ . The power law coefficient is  $\alpha = 1.65$ . The second plot shows the same for bank asset levels, with a power law coefficient of  $\alpha = 1.17$ .

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.

### 3.1.2 Centrality

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 institutions (SIFIs). To understand this feature of our network, we use several variants of the most common measure, centrality. First, centrality can simply be measured by the number of connections a node has, i.e., its degree; this is known as degree centrality. Of course, degree centrality ignores the fact that a node with few connections may still have a huge influence if it is connected to a node with many connections.<sup>7</sup> Degree centrality may be varied by computing degree to a chosen depth, say three levels deep, a parameter chosen at the discretion of the modeler.

A more general formulation is eigenvalue centrality (Bonacich, 1987; Bonacich and Lloyd, 2001), where centrality ( $c_i$ ) of a node is defined as a function of the centrality of the nodes

<sup>7</sup>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.

to which it is connected, through the network matrix,  $A$ . This leads to a circular system of  $n$  simultaneous equations:

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

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

$$\lambda c = A \cdot c \quad (2)$$

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

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

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

through a given node. Following [Freeman \(1977\)](#), betweenness centrality for a node  $v$  is defined as follows:

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

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

Interestingly, the results differ when considering betweenness centrality. Only one of the top 10 banks using this measure 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 geograph-

Table 2: Top ten banks by betweenness centrality.

1929: Bank Name and Location
First National Bank of Chicago (Chicago, IL)
Security First National Bank of Los Angeles (Los Angeles, CA)
Union Trust Company (Cleveland, OH)
American Trust Company (San Francisco, CA)
Citizens National Trust & Savings Bank (Los Angeles, CA)
Mississippi Valley Merchants State Trust Company (St. Louis, MO)
Mercantile Commerce Bank and Trust Company (St. Louis, MO)
Fifth Third Union Trust Company (Cincinnati, OH)
Mellon National Bank (Pittsburgh, PA)
The Philadelphia National Bank (Philadelphia, PA)
1934: Bank Name and Location
First National Bank of Chicago (Chicago, IL)
Security First National Bank of Los Angeles (Los Angeles, CA)
<i>First National Bank in St. Louis (St. Louis, MO)</i>
<i>The Pennsylvania Company (Philadelphia, PA)</i>
<i>Republic National Bank and Trust (Dallas, TX)</i>
Mellon National Bank (Pittsburgh, PA)
Mercantile Commerce Bank and Trust Company (St. Louis, MO)
<i>The Boatmen's National Bank (St. Louis, MO)</i>
<i>Harris Trust and Savings Bank (Chicago, IL)</i>
<i>City National Bank and Trust Company (Chicago, IL)</i>

ically 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, 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.<sup>8</sup> The Federal Reserve Act

---

<sup>8</sup>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.

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.<sup>9</sup> The Federal Reserve Act, as amended in 1917, required national and state-member banks to meet their reserve requirements entirely by holding deposits at their regional Federal Reserve Bank. By 1929, however, only 10% of state-chartered commercial banks had joined the Federal Reserve System.

Since roughly 90% had declined to join, much of the reserve pyramid remained in place in 1929 (Mitchener and Richardson, 2019). Nonmember banks continued to meet their state-mandated reserve requirements by holding interbank deposits at banks in one of the 63 reserve cities as well as Chicago and New York – the central reserve cities. They also held their excess reserves in these reserve-city banks, which they used to manage liquidity and offer a broader array of services to their clientele.<sup>10</sup> To a large degree, then, this pyramid structure was a relic of the national banking era (when regulations allowing reserve requirements to be met by holding them in larger-city banks were first imposed (Anderson et al., 2019), and the subsequent failure of the Federal Reserve System to convince all state-chartered banks to switch their charters and join the system after 1914 (Anderson et al., 2018)). Though the broad contours and shape 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 particular network topology, and in particular how they relate to systemic risk, we compare the diameter and fragility of the actual 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.<sup>11</sup> “Diameter” is defined as the maximal shortest path between any pair of nodes in the cluster for a non-directional

---

<sup>9</sup>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).

<sup>10</sup>Federal Reserve member banks also deposited excess reserves at correspondent banks in reserve and central reserve cities, since commercial correspondent accounts paid a higher interest rate (typically 2%) than Federal Reserve Banks (typically 0%). This was particularly true of reserve-city banks, which deposited their excess reserves in money-center banks in New York and Chicago. In June 1929, member banks held 93% of all interbank deposits in the United States. Nonmember banks held only 7%.

<sup>11</sup>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 László-Barabasi and Albert (1999).



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. 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.<sup>12</sup> The random network specified in this manner has a diameter of 12 and a fragility 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.

---

<sup>12</sup>We generated several random networks and the results align with the presented case.

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.<sup>13</sup>

## 4 Quantifying Systemic Risk

### 4.1 Deriving Composite Risk Scores

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

---

<sup>13</sup>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.

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;
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).<sup>14</sup>

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

$$C = a + \frac{1}{1 + BUF} \cdot b \quad (4)$$

where  $a = -8$  and  $b = 18$ . We can see that  $C \in (1, 10)$  because  $BUF \in (0, 1)$ . An increasing score implies greater risk. The mean credit risk score 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). 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 (6.17) and Continental Illinois (7.28) exceeded the mean of 5.65 in 1934.

---

<sup>14</sup>This is close to a bank's return on equity, however, because we do not observe dividends paid out, it is not identical to it. It was nevertheless used by banks to expand operations or write off losses relative to the book value of net worth. See [Carlson and Rose \(2015\)](#).

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

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

---

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

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

$$L = \ln(1 + Assets/Equity). \quad (5)$$

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

$$R = C \times L. \quad (6)$$

In the ensuing analysis of systemic risk, we focus on  $R$  since this metric has appealing properties. For example, because it is possible for firms with a high BUF to have low equity (and consequently high leverage), these firms would be quite risky, yet the measure  $C$  would

not assign them as such. Multiplying  $C$  by  $L$  compensates for this possibility. 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. 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.

## 4.2 Systemic Risk Per Bank

We combine the network adjacency matrix  $A$  (described in [Section 3.1](#)) with the composite risk score for each bank in the vector  $R$  to create a single measure of systemic risk per bank, extending and modifying the metrics proposed in [Das \(2016\)](#) and [Das et al. \(2019\)](#). Our approach allows one to empirically estimate “exposure” despite not knowing everything we might want about the financial network. (For example, data on balance-sheet linkages between financial institutions is often opaque or incomplete, both historically and today.) Systemic risk per bank,  $S$ , is thus defined as:

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

$$= \sqrt{\frac{R^\top}{n} \cdot A \cdot \frac{R}{n}} \tag{8}$$

$$= \sqrt{Q^\top \cdot A \cdot Q} \tag{9}$$

where  $n$ , as noted before, is the number of banks in the system, and superscript  $\top$  denotes the transpose of a vector or matrix. (Recall that  $R$  is an  $n$ -vector and  $A$  is a  $n \times n$  matrix. Thus,  $Q$  is an  $n$ -vector.) Division by  $n$  is a normalization used to measure systemic risk per financial institution and to account for the fact that the banking crises of the early 1930s drastically reduced the number of financial institutions in the network by 1934.  $S$  is an appropriate measure for our historical setting because it captures the physical interconnectedness between institutions and the direction of correspondent-respondent relationships.  $A$  is not symmetric

and thus accounts for the direction of relationships between banks in the network.

Equation (8) implies that systemic risk, as denoted by scalar quantity  $S$ , increases if the elements of  $R$  (individual bank risk) increase, holding  $n$  and  $A$  constant. Likewise, *ceteris paribus*, if the elements of  $A$  (interconnectedness of banks) increase, systemic risk per bank also increases. Note also that since the elements of  $R$  and  $A$  are all non-negative,  $S$  is also non-negative. The systemic risk measure,  $S$ , may be thought of as a network-weighted measure of composite credit risk in the banking system. We note that it can be decomposed into two components: (1) the amount emanating from individual bank risk and (2) that from network effects. If we replace the network matrix,  $A$ , with the identity matrix and recompute  $S$ , i.e.,  $S' = \sqrt{\sum_{i=1}^n R_i^2}$  then this measures composite emanating risk from individual bank risk only. The ratio  $S/S' \geq 1$  is a measure of systemic risk arising from network effects.

Plugging the values from the 1929 data into these equations, we find that the total systemic risk per bank,  $S$ , is 0.104. The ratio  $S/S' = 1.46$ , suggesting that the network effect amplifies systemic risk by a factor of 1.46. By itself, the value carries little meaning, but since it can be 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. Given average connectivity (measured by mean degree) and balance-sheet risk (measured by  $R$ ) are moving in opposite directions, this number shows that increased balance sheet risk more than offset the decline in connectivity. Note, however, that the measure  $S/S'$ , the network multiplier, is marginally higher at 1.53 in 1934 than in 1929.

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

of 0.004. Hence, the increase in  $S$  score from 0.104 in 1929 to 0.138 in 1934 is statistically significant.

To understand where risk was concentrated before and after the banking distress of the Great Depression, we can decompose systemic risk 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  $Q = [Q_1, Q_2, \dots, Q_n]^\top$ , the normalized value of  $R$ . We can apply Euler's homogenous function theorem and obtain the *risk decomposition equation*:

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

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

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

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

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 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: they provide additional perspective on how systemic risk changes due to a massive financial crisis.

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
The 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
<hr/>	
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



As a robustness check, we also recomputed the risk score in equation (6) 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), The National Bank of the Republic of Chicago, Fidelity National Bank and Trust Company (Kansas City), and Fletcher American National Bank (Indianapolis). The survival of most of the 20 ex ante systemically riskiest banks was buttressed by the fact that, on average, these banks had lower than average composite risk,  $R$ , in 1929. While they were central to the network, and thus “systemically important,” their better financial position and lower credit risk prior to the crisis allowed them to bend, but not break. Appendix Figure 7 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.<sup>15</sup> 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).<sup>16</sup> 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 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

---

<sup>15</sup>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).

<sup>16</sup>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

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.<sup>17</sup> 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%.

<sup>17</sup>RFC assistance is not the same as the bank being “quarantined.” Many banks failed despite receiving RFC assistance.

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 9 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 otherwise.<sup>18</sup> 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.4, we disentangle failures and mergers.

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

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

and

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

For both, the mapping from the latent to the observed data is  $y_i = 1\{y_i^* > 0\}$  and  $\varepsilon_i \sim N(0,1)$ . 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

---

<sup>18</sup>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.

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.<sup>19</sup> 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). Following Carlson and Mitchener (2006), the branching intensity variable is the share of banks operating branches in the state.

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. 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.

---

<sup>19</sup>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).

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 <sup>†</sup>
$M_1, M_2$	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 <sup>†</sup>
$M_1, M_2$	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 <sup>†</sup>

Note: County population, manufacturing establishments, and acres of cropland are from the 1930 *U.S. Census of Population, Manufacturing, and Agriculture*. <sup>†</sup>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.

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

In this section, we 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  $\beta$  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.<sup>20</sup>

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  $M_l$ :

$$f(y|M_l) = \prod_{i=1}^n f(y_i | \{y_j\}_{j < i}, M_l) \quad (14)$$

$$= \prod_{i=1}^n \int f(y_i | \{y_j\}_{j < i}, \beta_l, M_l) \pi(\beta_l | \{y_j\}_{j < i}, M_l) d\beta_l. \quad (15)$$

Equation 14 represents the marginal likelihood as the product of  $n$  one-step-ahead sequential predictive densities, which follows from the law of total probability. Equation 15 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

---

<sup>20</sup>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.

density,  $\pi(\beta|y)$ , based only on data up to the  $i$ th 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  $M_2$ .<sup>21</sup> 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  $M_1$ .

Table 7: Model Comparison Results for  $M_1$  and  $M_2$ .

	$M_1$	$M_2$
Log-Marginal Likelihood	-15342.06	-14982.69
Numerical Standard Error	(0.007)	(0.017)
Posterior Model Probability	$8.38 \times 10^{-157}$	$\approx 1$

While the marginal likelihood is the superior measure for sequential out-of-sample predictive fit, the in-sample classification rates give us straightforward and intuitive numbers. With the inclusion of network, composite risk, and interaction variables, outcomes for 325 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.

<sup>21</sup>The odds in favor of network measures over no network predictors is  $\approx 1.19 \times 10^{159} : 1$ . The chi-square test for confusion matrix differences between  $M_1$  and  $M_2$  is also highly significant with a p-value of zero.



### 5.3 Parameter Results and Covariate Effects

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. As shown in  $M_2$ , all 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 im-

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 10.

	$M_1$	$M_2$
Intercept	-1.056 (0.175)	0.028 (0.198)
Loans/Deposits	-0.021 (0.046)	-0.304 (0.047)
Bonds/Assets	1.088 (0.075)	0.732 (0.076)
LnAssets	0.188 (0.009)	0.150 (0.010)
EigenCent		3.006 (1.671)
Composite Risk		-0.060 (0.002)
SysRisk Percent		-7.175 (2.880)
Fed Member	0.025 (0.019)	0.029 (0.020)
Fed Member $\times$ SysRisk Percent		8.023 (2.866)
Branch Intensity	0.712 (0.215)	1.077 (0.241)
Branch Intensity $\times$ EigenCent		-5.182 (2.131)
Num Banks in County	-0.007 (0.004)	-0.011 (0.004)
Deposits/County Deposits	0.333 (0.059)	0.370 (0.060)
Central Reserve City	-1.025 (0.107)	-0.995 (0.108)
Reserve City	-0.357 (0.043)	-0.315 (0.042)
LnPopulation	-0.095 (0.013)	-0.084 (0.013)
Manufact per capita	0.475 (0.105)	0.563 (0.109)
Cropland per capita	-0.003 (0.001)	-0.003 (0.001)
Fed. Dist. FE	Yes	Yes
$n$	24,761	24,761

portance 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 the results for network position: 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 Vossmeier \(2018\)](#), 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:

$$\delta_{SysRisk} = \int \frac{\partial \Pr(y_i = 1|x, \beta)}{\partial x_{SysRisk}} f(x) \pi(\beta|y) dx d\beta. \tag{16}$$

We find that the marginal effect of a Fed member bank’s contribution to systemic risk is 0.269 and the marginal effect of a nonmember bank’s contribution to systemic risk is -2.556. The distributions of these average effects as a function of parameter uncertainty and units in the sample are presented in Figure 5.

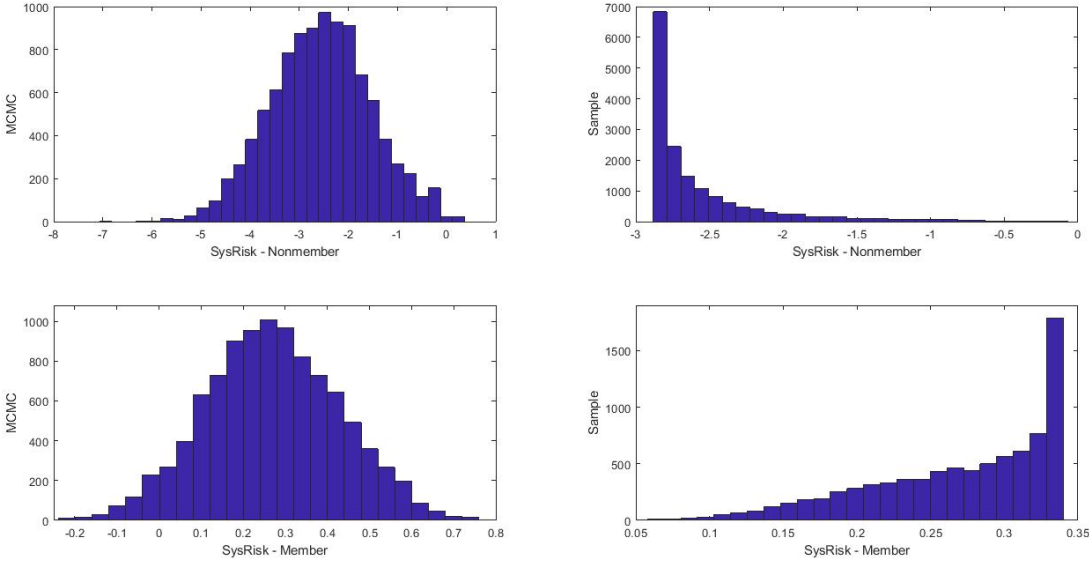


Figure 5: Marginal effects of systemic risk contribution for nonmembers (top) and members (bottom). Distributions of the average effect as a function of parameter uncertainty is on the left side and as a function of units in the sample is on the right side.

Thus, on average and all else equal, a marginal increase in systemic risk increases the probability of survival for Fed-members by 0.26%. On the other hand, a marginal increase in systemic risk for nonmembers decreases the probability of survival by 2.55%. 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 thereafter onto connected member banks.<sup>22</sup> 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).<sup>23</sup> 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 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 7 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 16. The derivative is taken with respect to  $x_{eigencent}$ , and this effect is computed for the subsample of banks

---

<sup>22</sup>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).

<sup>23</sup>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.

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 0.869 and the marginal effect of eigenvalue centrality in non-branching areas is 1.061, 22% higher. The distributions of these average effects as a function of parameter uncertainty and units in the sample are presented in Figure 6. Thus, as the intensity of branch banking in an area

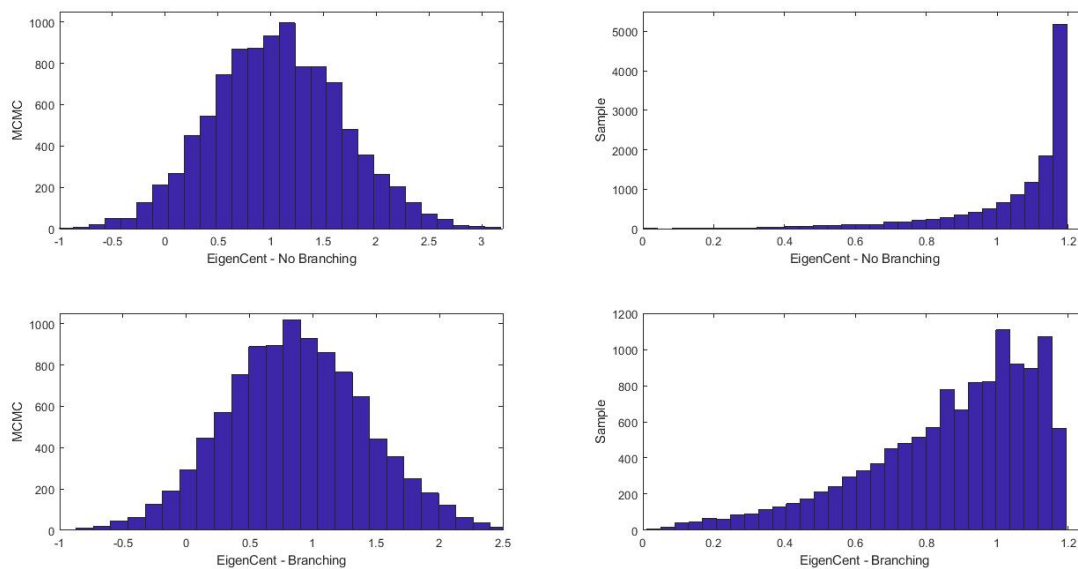


Figure 6: Marginal effects of eigenvalue centrality for non-branching areas (top) and branching areas (bottom). Distributions of the average effect as a function of parameter uncertainty is on the left side and as a function of units in the sample is on the right side.

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 rela-

tionship 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.

Simple robustness checks, maximum likelihood estimates (with standard error adjustments), and information criteria for the full sample probit specification are provided in Appendix A.3. We find that the estimated coefficients are robust to including state fixed effects; however, the fixed effects lead to overfitting as the information criteria does not favor the specification. Therefore, the results presented in this main body are the strongest, and most supported by the data. Furthermore, Appendix A.4 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 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, bank merger, and bank 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. 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. 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.

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.

Finally, our computed systemic risk scores are a potentially important input into future research on the Great Depression. For example, if one were able to obtain data and quantify the banks that were involved in local, regional, and national panics in the early 1930s, it would be possible to examine whether systemic risk measures predict whether banks were more likely to be run during panic periods and further explore the extent to which these liquidity-constrained banks were *ex ante* ones with weak balance sheets (as emphasized in [Calomiris and Mason \(2003\)](#)) or were particularly central to the network.



## References

- Abrams, B. and Settle, R. (1993), “Pressure-group influence and institutional change: Branch-banking legislation during the Great Depression,” *Public Choice*, 77, 687–705.
- Acemoglu, D., Ozdaglar, A., and Tahbaz-Salehi, A. (2015), “Systemic Risk and Stability in Financial Networks,” *American Economic Review*, 105, 564–608.
- Acharya, V. V., Pedersen, L. H., Philippon, T., and Richardson, M. (2017), “Measuring Systemic Risk,” *Review of Financial Studies*, 30, 2–47.
- Allen, F. and Gale, D. (2000), “Financial Contagion,” *Journal of Political Economy*, 108, 1–33.
- Allen, F., Babus, A., and Carletti, E. (2010), “Financial Connections and Systemic Risk,” Tech. Rep. w16177, National Bureau of Economic Research, Cambridge, MA.
- Anderson, H., Calomiris, C. W., Jaremski, M., and Richardson, G. (2018), “Liquidity Risk, Bank Networks, and the Value of Joining the Federal Reserve System,” *Journal of Money, Credit and Banking*, 50, 173–201.
- Anderson, H., Paddrik, M., and Wang, J. (2019), “Bank Networks and Systemic Risk: Evidence from the National Banking Acts,” *American Economic Review*, forthcoming.
- Arthur, W. (1988), “Self-reinforcing Mechanisms in Economics,” in *The Economy as an Evolving Complex System*, Addison Wesles.
- Arthur, W. (1989), “Competing Technologies, Increasing Returns, and Lock-in by Historical Events,” *The Economic Journal*, 99, 116–131.
- Barabasi, A.-L. (2002), *Linked: The New Science of Networks*, Basic Books.
- Barabasi, A.-L. and Bonabeau, E. (2003), “Scale-Free Networks,” *Scientific American*, 288, 60–69.
- Beggs, A. and Klemperer, P. (1992), “Multi-period Competition with Switching Costs,” *Econometrica*, 60, 651–666.
- Billio, M., Getmansky, M., Lo, A. W., and Pelizzon, L. (2012), “Econometric measures of connectedness and systemic risk in the finance and insurance sectors,” *Journal of Financial Economics*, 104, 535–559.
- Bisias, D., Flood, M., Lo, A. W., and Valavanis, S. (2012), “A Survey of Systemic Risk Analytics,” *Annual Review of Financial Economics*, 4, 255–296.
- Board of Governors, F. R. S. (1936), *Bank Suspensions, 1892-1935*.
- Bonacich, P. (1987), “Power and Centrality: A Family of Measures,” *American Journal of Sociology*, 92, 1170–1182.

- Bonacich, P. and Lloyd, P. (2001), “Eigenvector-like measures of centrality for asymmetric relations,” *Social Networks*, 23, 191–201.
- Brownlees, C., Chabot, B., Ghysels, E., and Kurz, C. (2017), “Back to the Future: Back-testing Systemic Risk Measures during Historical Bank Runs and the Great Depression,” Tech. Rep. 12178, C.E.P.R. Discussion Papers.
- Brunetti, C., Harris, J., Mankad, S., and Michailidis, G. (2019), “Interconnectedness in the Interbank Market,” *Journal of Financial Economics*, forthcoming.
- Burdick, D., Hernandez, M. A., Ho, H., Koutrika, G., Krishnamurthy, R., Popa, L., Stanoi, I., Vaithyanathan, S., and Das, S. R. (2011), “Extracting, Linking and Integrating Data from Public Sources: A Financial Case Study,” *IEEE Data Eng. Bull.*, 34, 60–67.
- Caballero, R. and Simsek, A. (2013), “Fire Sales in a Model of Complexity,” *Journal of Finance*, 68, 2549–2587.
- Calomiris, C. and Mason, J. (1997), “Contagion and Bank Failures During the Great Depression: The June 1932 Chicago Banking Panic,” *American Economic Review*, 87, 863–883.
- Calomiris, C., Jaremski, M., and Wheelock, D. (2019), “Interbank Connections, Contagion, and Bank Distress in the Great Depression,” *SSRN Working Paper*.
- Calomiris, C. W. and Carlson, M. (2017), “Interbank networks in the National Banking Era: Their purpose and their role in the Panic of 1893,” *Journal of Financial Economics*, 125, 434–453.
- Calomiris, C. W. and Mason, J. R. (2003), “Fundamentals, Panics, and Bank Distress During the Depression,” *American Economic Review*, 93, 1615–1647.
- Calomiris, C. W., Mason, J. R., Weidenmier, M., and Bobroff, K. (2013), “The Effects of the Reconstruction Finance Corporation Assistance on Michigan’s Banks’ Survival in the 1930s,” *Explorations in Economic History*, 50, 525–547.
- Carlson, M. (2004), “Are Branch Banks Better Survivors? Evidence from the Depression Era,” *Economic Inquiry*, 42, 111–126.
- Carlson, M. and Mitchener, K. (2006), “Branch Banking, Bank Competition, and Financial Stability,” *Journal of Money, Credit and Banking*, 38, 1293–1328.
- Carlson, M. and Rose, J. (2015), “Credit Availability and the Collapse of the Banking Section in the 1930s,” *Journal of Money, Credit and Banking*, 47, 1239–1271.
- Carlson, M. and Wheelock, D. (2016), “Interbank Markets and Banking Crises: New Evidence on the Establishment and Impact of the Federal Reserve,” *American Economic Review*, 106, 533–537.
- Carlson, M. and Wheelock, D. (2018), “Did the Founding of the Federal Reserve Affect the Vulnerability of the Interbank System to Contagion Risk,” *Journal of Money, Credit and Banking*, 50, 1711–1750.

- Chib, S. (1995), “Marginal Likelihood from the Gibbs Output,” *Journal of the American Statistical Association*, 90, 1313–1321.
- Chib, S. and Jeliazkov, I. (2001), “Marginal Likelihood from the Metropolis-Hastings Output,” *Journal of the American Statistical Association*, 96, 270–281.
- Choudhary, V., Currim, I., Dewan, S., Jeliazkov, I., Mintz, O., and Turner, J. (2017), “Evaluation Set Size and Purchase: Evidence from a Product Search Engine,” *Journal of Interactive Marketing*, 37, 16–31.
- Curtis, J. (1930), “The Turning Financial Worm,” in *Chain, Group and Branch Banking*, H.W. Wilson Co.
- Das, S. R. (2016), “Matrix Metrics: *Network-Based Systemic Risk Scoring*,” *The Journal of Alternative Investments*, 18, 33–51.
- Das, S. R., Kim, S., and Ostrov, D. (2019), “Dynamic Systemic Risk Networks,” *Journal of Financial Data Science*, 1, 141–158.
- Dasgupta, A. (2004), “Financial Contagion through Capital Connections: A Model of the Origin and Spread of Bank Panics,” *Journal of the European Economic Association*, 2, 1049–1084.
- Dupont, B. (2017), “Bank Networks and Suspensions in the 1893 Panic: Evidence from the State Banks and their Correspondents in Kansas,” *Financial History Review*, 24, 265–282.
- Elliott, M., Golub, B., and Jackson, M. O. (2014), “Financial Networks and Contagion,” *American Economic Review*, 104, 3115–3153.
- Farrell, J. and Shapiro, C. (1989), “Optimal Contracts with Lock-in,” *American Economic Review*, 79, 51–68.
- Freeman, L. C. (1977), “A Set of Measures of Centrality Based on Betweenness,” *Sociometry*, 40, 35–41.
- Freixas, X., Parigi, B. M., and Rochet, J.-C. (2000), “Systemic Risk, Interbank Relations, and Liquidity Provision by the Central Bank,” *Journal of Money, Credit and Banking*, 32, 611–638.
- Friedman, M. and Schwartz, A. J. (1963), *A Monetary History of the United States, 1867-1960*, Princeton University Press.
- Gabaix, X., Gopikrishnan, P., Plerou, V., and Stanley, H. E. (2003), “A theory of power-law distributions in financial market fluctuations,” *Nature*, 423, 267–270.
- Gallini, N. and Karp, L. (1989), “Sales and Consumer Lock-in,” *Economica*, 56, 279–294.
- Gorton, G. and Tallman, E. (2018), *Fighting Financial Crises: Learning from the Past*, University of Chicago Press.

- Greenberg, E. (2008), *Bayesian Econometrics*, Cambridge University Press.
- Heitfield, E., Richardson, G., and Wang, S. (2017), “Contagion During the Initial Banking Panic of the Great Depression,” *NBER Working Paper 23629*.
- James, J. A. and Weiman, D. F. (2010), “From Drafts to Checks: The Evolution of Correspondent Banking Networks and the Formation of the Modern U.S. Payments System, 1850-1914,” *Journal of Money, Credit and Banking*, 42, 237–265.
- James, J. A. and Weiman, D. F. (2011), “The National Banking Acts and the Transformation of New York City Banking During the Civil War Era,” *The Journal of Economic History*, 71, 338–362.
- Jaremski, M. and Wheelock, D. (2019), “The Founding of the Federal Reserve, the Great Depression and the Evolution of the U.S. Interbank Network,” *FRB St. Louis Working Paper No. 2019-2*.
- Jeliazkov, I. and Vossmeier, A. (2018), “The Impact of Estimation Uncertainty on Covariate Effects in Nonlinear Models,” *Statistical Papers*, 59, 1031–1042.
- Jeliazkov, I., Graves, J., and Kutzbach, M. (2008), “Fitting and comparison of models for multivariate ordinal outcomes,” in *Bayesian Econometrics*, vol. 23 of *Advances in Econometrics*, pp. 115–156, Emerald Group Publishing Limited.
- Jones, J. H. (1951), *Fifty billion dollars: my thirteen years with the RFC, 1932-1945*, Macmillan Co., New York, OCLC: 233209.
- Kemmerer, E. W. (1922), *The ABC of the Federal Reserve System; why the federal reserve system was called into being, the main features of its organization, and how it works.*, Princeton University Press, Princeton.
- Klemperer, P. (1987a), “The Competitiveness of Markets with Consumer Switching Costs,” *Rand Journal of Economics*, 18, 138–150.
- Klemperer, P. (1987b), “Markets with Consumer Switching Costs,” *Quarterly Journal of Economics*, 102, 375–394.
- Lasszlo-Barabasi, A. and Albert, R. (1999), “Emergence of Scaling in Random Networks,” *Science*, 286, 509–512.
- Merton, R. C. (1974), “On the Pricing of Corporate Debt: The Risk Structure of Interest Rates,” *The Journal of Finance*, 29, 449–470.
- Mitchener, K. (2005), “Bank Supervision, Regulation, and Instability During the Great Depression,” *Journal of Economic History*, 65, 152–185.
- Mitchener, K. J. (2007), “Are Prudential Supervision and Regulation Pillars or Financial Stability? Evidence from the Great Depression,” *Journal of Law and Economics*, 50, 273–302.

- Mitchener, K. J. and Richardson, G. (2019), “Network Contagion and Interbank Amplification during the Great Depression,” *Journal of Political Economy*, April.
- Nadler, M. and Bogen, J. (1933), *The Banking Crisis: The End of an Epoch*, New York: Dodd, Mead and Co.
- Redenius, S. A. (2007), “Designing a national currency: antebellum payment networks and the structure of the national banking system,” *Financial History Review*, 14.
- Richardson, G. (2007), “The Check is in the Mail; Correspondent Clearing and the Collapse of the Banking System, 1930 to 1933,” *The Journal of Economic History*, 67, 643–671.
- Richardson, G. and Troost, W. (2009), “Monetary Intervention Mitigated Banking Panics During the Great Depression: Quasi-Experimental Evidence from a Federal Reserve District Border 1929-1933,” *Journal of Political Economy*, 117, 1031–1073.
- Sprague, O. M. W. (1910), *History of Crises under the National Banking System*, U.S. Government Printing Office.
- Tierney, L. (1994), “Markov Chains for Exploring Posterior Distributions,” *The Annals of Statistics*, 22, 1701–1728.
- Vossmeyer, A. (2016), “Sample Selection and Treatment Effect Estimation of Lender of Last Resort Policies,” *Journal of Business and Economic Statistics*, 34, 197–212.
- Wheelock, D. (2010), “Lessons Learned? Comparing the Federal Reserves Responses to the Crises of 1929-1933 and 2007-2009,” *Federal Reserve Bank of St. Louis Review*, 92, 89–107.
- White, N., E. (1983), *The Regulation and Reform of the American Banking System, 1900-1929*, Princeton University Press, Princeton, N.J.
- Wicker, E. (1996), *The Banking Panics of the Great Depression*, Cambridge University Press, Cambridge.
- Ziebarth, N. (2013), “Identifying the Effects of Bank Failures from a Natural Experiment in Mississippi During the Great Depression,” *American Economic Journal: Macroeconomics*, 5, 81 – 101.

## A Appendix

### A.1 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 7 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.

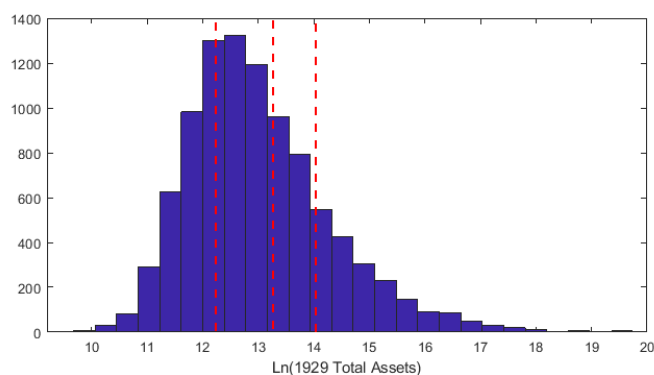


Figure 7: Histogram of bank exits from the network by 1934 as a function of (log) total assets in 1929. The red dashed lines represent the 25th, 50th, and 75th percentiles of the asset distribution of the entire banking population (not just exits) in 1929.

## A.2 Counterfactuals

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

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

### A.3 MLE Results

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 S.E. reports the MLE results with robust standard errors clustered at the county level, which does not change the statistical significance of our parameter estimates. The last column  $M_3$  reports the results for the model with state fixed effects. The main results are preserved, but the information criteria suggest overfitting. Therefore, we focus our analysis on  $M_2$ .

Table 10: Maximum likelihood estimates and standard errors are presented for  $M_1$  and  $M_2$  (full sample). \*\*\* implies significance at the 1% level, \*\* implies significance at the 5% level, \* implies significance at the 10% level.

	$M_1$	$M_2$	S.E.	$M_3$
Intercept	-1.055 (0.188)***	0.019 (0.200)	(0.276)	-0.232 (0.396)
Loans/Deposits	-0.021 (0.048)	-0.304 (0.050)***	(0.053)***	-0.349 (0.051)***
Bonds/Assets	1.089 (0.078)***	0.729 (0.080)***	(0.088)***	0.661 (0.083)***
LnAssets	0.187 (0.009)***	0.150 (0.011)***	(0.012)***	0.152 (0.011)***
EigenCent		3.200 (1.886)*	(1.902)*	4.742 (1.949)**
Composite Risk		-0.060 (0.002)***	(0.002)***	-0.059 (0.002)***
SysRisk Percent		-8.807 (3.513)**	(4.185)**	-7.308 (3.556)**
Fed Member	0.025 (0.020)	0.025 (0.022)	(0.027)	0.032 (0.022)
Fed Member $\times$ SysRisk Percent		9.606 (3.4488)***	(4.218)**	7.892 (3.530)**
Branch Intensity	0.709 (0.224)**	1.095 (0.258)***	(0.308)***	12.350 (5.578)**
Branch Intensity $\times$ EigenCent		-5.532 (2.316)**	(2.132)**	-5.043 (2.492)**
Num Banks in County	-0.007 (0.003)*	-0.011 (0.004)***	(0.004)***	-0.005 (0.004)
Deposits/County Deposits	0.332 (0.062)***	0.369 (0.063)***	(0.068)***	0.382 (0.065)***
Central Reserve City	-1.022 (0.111)***	-0.989 (0.114)***	(0.156)***	-0.886 (0.118)***
Reserve City	-0.357 (0.045)***	-0.312 (0.046)***	(0.068)***	-0.323 (0.047)***
LnPopulation	-0.095 (0.014)***	-0.084 (0.014)***	(0.020)***	-0.089 (0.015)***
Manufact per capita	0.474 (0.111)***	0.559 (0.112)***	(0.168)***	0.137 (0.125)
Cropland per capita	-0.003 (0.001)**	-0.003 (0.001)**	(0.003)*	-0.001 (0.001)
Fed. Dist. FE	Yes	Yes		Yes
State FE	No	No		Yes
$n$	24,761	24,761		24,761
$BIC$	30645.94	29944.58		30081.87



## A.4 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  $M_2$  in the previous section. However, the outcome variable is now ordered and defined as:

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

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  $\beta$  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 11: Model comparison results for the two ordered models.

	$M_1$	$M_2$
$n$	7,525	7,525
Log-Marginal Likelihood	-7684.78	-7407.06
Posterior Model Probability	$2.44 \times 10^{-121}$	$\approx 1$

Table 11 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 previous section and point to an additional important implication: a specification including our new measures not only improves the prediction of bank failures, but also those for bank mergers, an important observed outcome in most financial crises.