How do Financial Crises Redistribute Risk?

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Abstract

We examine how financial crises redistribute risk, employing novel empirical methods and micro data from the largest financial crisis of the 20^{th} century – the Great Depression. Using balance-sheet and systemic risk measures at the bank level, we build an econometric model with incidental truncation that jointly considers bank survival, the type of bank closure (consolidations, absorption, and failures), and changes to bank risk. Despite roughly 9,000 bank closures, risk did not leave the financial system; instead, it increased. We show that risk was redistributed to banks that were healthier prior to the financial crisis. A key mechanism driving the redistribution of risk was bank acquisition. Each acquisition increased the balance-sheet and systemic risk of the acquiring bank by 25%. Our findings suggest that financial crises do not quickly purge risk from the system, and that merger policies commonly used to deal with troubled financial institutions during crises have consequences for financial stability.

JEL classification: G21, C30, N12.

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1 Introduction

On the eve of financial crises, risks are elevated, often characterized by the peak of a leverage cycle (Geanakoplos, 2009; Schularick and Taylor, 2012). In the aftermath of a crisis, where does risk go? Does it leave the system quickly or is it simply redistributed? Financial crises generate flux, leading to failures and mergers in the financial sector; however, their effect on the riskiness of the financial system is ambiguous. On the one hand, a financial crisis could have a "cleansing effect," removing risks associated with poorly managed financial institutions from the system through closures, perhaps even leading to productivity-enhancing reallocations that can occur during periods of slack (Gropp et al., 2020; Foster et al., 2016). In policy circles, this view dates back at least to the "liquidationists" of the 1930s, which included Secretary of the Treasury Andrew Mellon, who according to U.S. President Herbert Hoover argued in favor of "purging the rottenness out of the system" during the crisis of the Great Depression (Hoover, 1951). Among economists, antecedents of the cleansing effect include Schumpeter (1942) and particularly von Mises (1949), who highlighted the need to correct misallocations arising from the banking sector. On the other hand, due to contagious bank runs and panics, it is possible that less risky banks also close, furthering market instabilities and inefficiencies. Just as important, it is also well documented that mergers among financial firms increase during crisis periods (Wheelock, 2011). As a result, rather than risk leaving the system, it may simply get redistributed. Weak or poorly managed financial institutions may be absorbed by remaining firms, leading to a shift in the location of risk, but not resulting in an overall reduction in risk in the financial system – an outcome that can be exacerbated by regulatory interventions meant to save "too big to fail banks" during crises. For example, evidence from corporate finance suggests that mergers can increase default-risk probabilities for acquiring firms even considering potential diversification benefits arising from mergers (Furfine and Rosen, 2011).

Since theory suggests risk can either rise or fall in the financial system based on which firms close and how they do so (e.g., failure, merger, etc), understanding how risk changes as a result of a financial crisis is ultimately an empirical question. However, answering this question requires surmounting significant data and methodological hurdles. For example, drawing inferences about the relationship between mergers and risk using data from recent crises (such as the global financial crisis of the late 2000s) is challenging because financial institutions are incentivized to merge given the existence of implicit regulatory backstops in the financial system (e.g., "too big to fail" policies may encourage banks to engage in mergers that increase moral hazard) and because regulators can compel them to do so during crises (e.g., through so-called "shotgun marriages" and as seen in the recent merger between UBS and Credit Suisse). Further, regulators are often quick to instruct and support financial institutions to build liquidity and capital buffers, endogenously changing the composition of balance sheets. Methodological challenges are similarly daunting because researchers must jointly account for the bank survival selection mechanism as well as the nonrandom type of bank closure in order to understand the mechanisms driving changes in risk.

To examine how risk changes and is redistributed in the aftermath of financial crises, we construct a comprehensive, systemwide data set from a period that predates widespread government safety nets and federal regulatory bank merger policies – the U.S. Great Depression. We develop new empirical methods that account for crisis-induced changes in risk as well as the role that mergers and failures play in redistributing risk. Using a microeconomic data set that covers the entire commercial banking system, more than 24,000 banks, we examine changes to the financial system just prior to the Depression and after the conclusion of the financial distress of the early 1930s. We introduce bank-level measures of balance-sheet risk and systemic risk, and track all consolidations, absorptions, and failures that occur during the financial crisis. We then develop a trivariate incidental truncation model that jointly considers bank closure, the type of closure, and changes to bank risk. Our econometric model and data allow us to estimate relationships between failures, mergers, and risk for the entire banking system, and precisely model the redistribution of risk.

The Great Depression is an attractive setting to study this question for several reasons. First and foremost, mergers and acquisitions by financial institutions were largely free of government interference during this period, so it can serve as a benchmark for understanding how unassisted mergers affect risk. Second, the early 1930s were a period of considerable flux in the banking system: more than 3,000 banks were acquired or merged and more than 6,000 failed. These changes to the banking system provide spatial and temporal variation that, in turn, permit us to identify how mergers and failures influenced balance sheet and systemic risk. Finally, the Great Depression is of interest in its own right. Though much has been written about banking distress in this period, an empirical analysis of whether mergers and failures raised or lowered risk in the system has yet to be written. We also aim to fill this lacuna.

Our micro results show that, in the year following the conclusion of the banking crisis, balance sheet risk and system risk are higher, on average, across all surviving banks. The raw data show a 33% increase in systemic risk. A key mechanism driving this change during our sample period is acquisitions. High-risk exiting banks were often absorbed by larger, more connected acquiring banks, redistributing risk to once healthier banks. We find that for each bank acquired, risk at acquiring banks increased by 25%. Since roughly 10% of the banks surviving the Great Depression were acquirers, this mechanism affected more than 1,500 banks – providing a plausible channel through which risk rose in the wake of the crisis. Among the largest 100 banks, the 33 acquiring banks contributed 8% to the overall change in systemic risk in the banking system whereas the 67 largest banks that did not acquire another bank actually reduced overall systemic risk by 2%. While much of the increase in systemic risk occurred at the largest banks, we find that acquirers across the size distribution positively influenced risk changes. Moreover, mergers on the periphery, between smaller and medium-sized banks often located in the same city, figured prominently in raising balance-sheet risk. Our findings thus highlight how financial crises can redistribute various types of risk differently. The trivariate incidental truncation model proves important. We show that relatively large biases in the estimated effects of acquisitions arise when the nonrandom bank survival selection mechanism is ignored. Furthermore, we demonstrate that the determinants of merger outcomes, relative to failures, have both spatial and temporal dependence, which the trivariate model conveniently captures.

From the macro perspective, our results show that in a mostly unfettered and unregulated environment, and even when thousands of banks are allowed to fail, risk is not quickly purged from the system. Instead, we find that risk remains in the system, and even increases, shifting to once healthier banks through merger processes. Therefore, we do not find support for "cleansing effects" – at least in the immediate aftermath of a financial crisis. Although the financial system has undergone important changes in the past 100 years, including the growth of non-bank entities, commercial banks are still a central part of the financial system and a common source of distress (as borne out by events in March 2023), and mergers continue to be a common response to crises. Our analysis sheds light on both of these elements of banking crises. First, in an environment of existing financial regulation and responses to banking crises by governments, it can be difficult to measure how much risk is due to banks changing their behavior versus other influences. Our study provides a low-regulation setting that can be used as a benchmark for understanding whether crises reduce risk. Second, our research fills a gap in the understanding of the role that mergers play in redistributing risk, which to this point has received little attention from academic researchers, but nevertheless can have important policy implications since a common regulatory solution during crises is to "marry" good banks with bad banks. In these instances, regulators often propose loss-sharing arrangements with acquiring institutions in order to address financial stability considerations (e.g., First Republic Bank). Our research formalizes the magnitude of potential risk changes due to acquisitions and provides a framework that assesses whether these policy responses are warranted.

We contribute to several areas of current research. Scholars have long been interested in understanding how crises affect financial stability (Carletti et al., 2002). Recent advances in the measurement of systemic risk have brought renewed scholarly interest to this topic, especially as it relates to the financial distress of the late 2000s and the Global Financial Crisis (GFC). A key area of work assesses whether regulations aimed at reducing risk ended up doing so in the wake of the 2007-8 crisis. For example, using market-based measures of risk and focusing on large, publicly traded financial institutions, Sarin and Summers (2016) find that risk rose among these institutions in spite of regulatory efforts to reduce it.[1] On the other hand, Duffie (2018) reviews the post-crisis global (G20) bank capital reforms, and reports that they have largely been successful in making institutions more resilient and stable, but at the cost of liquidity. Other related papers bring attention to the effect of mergers on systemic risk before and after the GFC. Weiss et al. (2014) report risk increased whereas Maslaka and Senel (2022) report risk decreased as a result of mergers and increased concentration.

We contribute to this research in several ways. First, we examine changes in overall risk from another large financial crisis, indeed the largest financial crisis of the 20$^{\text{th}}$ century and, in so doing, provide evidence on changes in risk for a mostly unfettered regulatory environment that can be used as a benchmark. Studying the less-regulated environment of the Great Depression provides a new perspective for analyzing these issues. Second, whereas a large literature exists on how mergers affect market concentration and competition (see Berger et al. (2004) for a review), comparatively little is known about how mergers affect financial stability risks. The few papers that address it (noted above) present mixed evidence. The relative dearth of research in this area is somewhat

[1] Relatedly, Calluzzoa and Dong (2015) find that while individual institutions have become less risky between 2005 and 2011, the market is more vulnerable to systemic contagion.

surprising since the passage of Dodd-Frank Act in 2010 requires federal bank regulators to consider financial stability when evaluating proposed mergers and acquisitions. Our study complements research on the GFC by exploring a more generalizable empirical setting to understand how mergers affect risk when they are unassisted and not incentivized by government regulations – a benchmark that may be important for regulators seeking information on how mergers affect macroprudential objectives. Third, our data and methods allow us to consider how risk changes across the entire banking system rather than subsets, such as publicly-traded firms which, in our period, would yield a small and non-representative sample of banks. Analyzing the full distribution of banks is critical for understanding how risk is altered and redistributed by crises since flux often occurs on the periphery — outside of big city banks. Mergers and failures in smaller and medium-sized cities and in rural areas were significant in our sample period as well as in more recent crisis periods (Astrid, 2006; Wheelock, 1995, 2011).

Our research also contributes to the understanding of the Great Depression. Despite the voluminous scholarship on banking distress in the early 1930s, surprisingly little has focused on changes to bank risk over time and the role of bank mergers. Thus far, research has documented that bank mergers and consolidations were an important feature of changes in the financial services industry in the early 1930s (FRB, 1937; White, 1985; Richardson, 2007) and that they offered a means for banks to resolve difficulties and avoid failure (Carlson, 2010). Our contribution is to provide an evaluation of risk changes by constructing a new micro data set that tracks when and where consolidations and absorptions occurred and then examining jointly the impact of mergers and failures on risk changes. To our knowledge, our study is the first to combine these two phenomena to understand how the banking distress of the Great Depression affected the overall risk in the banking system and, specifically, how mergers and failures redistributed it. Contrary to the predictions of the "liquidationists," we show that risk rose as a result of the crisis, primarily because acquiring banks took on additional risk.

Lastly, our econometric work contributes to the literature on potential outcome and sample selection models (see van Hasselt (2014) and Li and Tobias (2014) for a review). These models, in conjunction with multiple discrete outcomes, can be difficult to estimate because of the intractability of the likelihood function. Related work by Chib (2007) and Chib et al. (2009) show how the likelihood function for these models can be built without the joint distribution of the potential outcomes and without simulation of the missing outcomes. We combine the strategies from these streams of research and construct a bank-level model that contains a system of three equations – one bank survival selection mechanism and two treatment response outcomes (risk changes for banks that survive and exit type for banks that exit). These outcomes are jointly modeled and simultaneously estimated, allowing for a flexible dependence structure among the outcomes. We advance existing models in this area by accommodating both binary and ordered outcome variables. In doing so, we overcome the need for extra simulation by adapting the location and scaling restrictions necessary for unique outcome probabilities and present an efficient Bayesian estimation algorithm.

2 Methodology

2.1 Joint Model

In this section, we develop an incidental truncation model that can be used to consider several common features of banking crises. First, crises are broadly characterized by survival and exits. If a bank exits, how does it decide to do so: does it fail or does it get acquired? If it survives, is it a bank that acquires exiting banks or does it stand pat? All of these decisions ultimately affect the risk in the banking system. Our modeling framework accounts for these linked decisions.

The modeling framework is tailored to this application in order to overcome several hurdles. First, changes to balance sheet or systemic risk are only observed for banks that survive the crisis. Therefore, we need the model to accommodate the nonrandom survival selection mechanism. Second, banks can exit the sample through consolidation, absorption, or failure. Jointly modeling the determinants of these different outcome categories is important in order to understand the role mergers played in altering risk during the crisis. Lastly, bank survival and exit type are discrete outcomes. Thus, the model needs to be estimable for multivariate limited dependent variables. Motivated by these challenges, we develop a trivariate incidental truncation model and a computationally efficient estimation algorithm.

Figure 1 graphically illustrates the three-equation, incidental truncation model. Bank survival is a binary {0,1} variable that takes the value 1 if the bank survives between 1929 and 1934 and 0 if the bank closes or exits the sample in that period. Equation (1) is the initial selection mechanism and the outcome is observed for every bank in the sample. For banks that survive over the sample

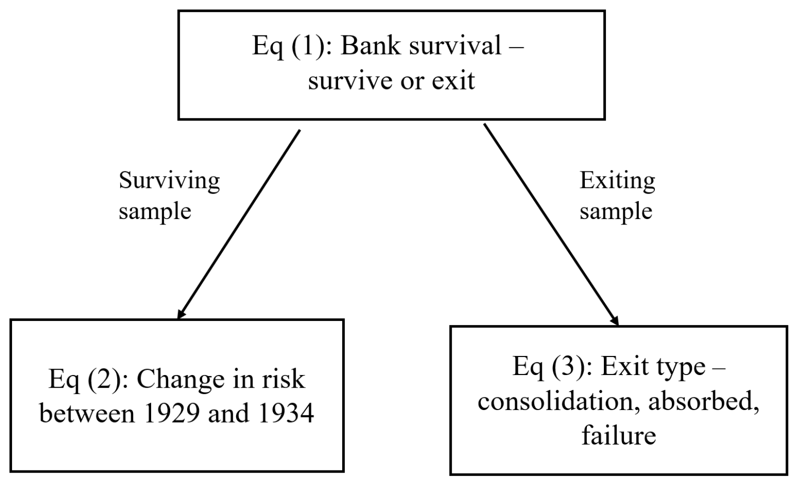

Figure 1: Graphical presentation of the trivariate system with incidental truncation.

period, we then observe Equation (2), which is a bank's change in risk between 1929 and 1934. We develop two measures for bank risk, balance-sheet risk and systemic risk, which are detailed in Section 3. For banks that exit between 1929 and 1934, we instead observe their exit type, Equation (3), where type is defined by the ordered outcome of consolidation, absorption, or failure. Because exit type is only observed for exiting banks and the change in risk is only observed for surviving banks, we have two bivariate systems. The one that is observed for a given bank depends on the selected sample. Thus, it follows that one must use a model of incidental truncation, i.e., sample selection or informative missingness.

The model structure is similar to that of treatment response or potential outcome frameworks (Roy, 1951; Rubin, 1978; Heckman and Honoré, 1990; Poirier and Tobias, 2003; Chib, 2007). It is not identical, however, because the outcomes for Equations (2) and (3) are not the same, as is usually the case for treatment and control groups. The model is also similar to sample selection frameworks (Heckman, 1976, 1979; Chib et al., 2009; van Hasselt, 2011; Li, 2011). However, unlike those, we observe an outcome for the exiting sample, which is important to capture in the joint setting. Variation in exit type is linked to the survival selection mechanism and, thus, communicates with changes to risk as the system is simultaneously estimated. An additional benefit of this modeling structure is that we retain separate equations for the surviving and exiting bank samples. Doing so allows us to build unique conditioning sets. For surviving banks, we condition on changes to nearby banking conditions that occur between 1929 and 1934. For exiting banks, we condition on nearby bank performance in the years prior to a particular bank's exit, given we have already controlled for the exit selection.

The model stemming from Figure 1 is defined by three equations with one selection mechanism and two response outcomes. For observations $i = 1, ..., n$:

$$\begin{aligned}
&\text{(Full sample)} & y_{i1}^* &= \boldsymbol{x}_{i1}'\boldsymbol{\beta}_1 + \varepsilon_{i1} &(1)\\
&\text{(Surviving sample)} & y_{i2}^* &= \boldsymbol{x}_{i2}'\boldsymbol{\beta}_2 + \varepsilon_{i2} &(2)\\
&\text{(Exiting sample)} & y_{i3}^* &= \boldsymbol{x}_{i3}'\boldsymbol{\beta}_3 + \varepsilon_{i3}. &(3)
\end{aligned}$$

The notation y_i^* represents latent data that are related to the observed outcomes. The outcome for the first equation is binary and is observed for every bank in the sample:

$$y_{i1} = \begin{cases} 1 & \text{if } y_{i1}^* > 0, \text{ Bank survives between 1929 and 1934} \\ 0 & \text{if } y_{i1}^* \leq 0, \text{ Bank exits between 1929 and 1934.} \end{cases} \tag{4}$$

The outcome for the second equation is the change in bank i's risk between 1929 and 1934. We develop two measures for risk – balance-sheet risk and systemic risk – with further details discussed in Section 3. The change in risk is a continuous outcome, i.e., $y_{i2}^* = y_{i2}$, and is only observed for the selected sample of surviving banks. The outcome for the third equation is the exit type. Exit type is ordered (as described in the data section, Section 3) and is only observed for the sample of exiting banks:

$$y_{i3} = \begin{cases} 3 & \text{if } \gamma_2 < y_{i3}^* < \infty, \text{ Consolidation} \\ 2 & \text{if } \gamma_1 < y_{i3}^* \leq \gamma_2, \text{ Absorbed} \\ 1 & \text{if } -\infty < y_{i3}^* \leq \gamma_1, \text{ Failure.} \end{cases} \tag{5}$$

The covariates in $\boldsymbol{x}_{i1}$ are measured in 1929 and include controls for balance-sheet ratios, bank size (log of total assets), town and county characteristics, regulatory variables, a market share of deposits, interbank network controls, and Federal Reserve district indicators. The variables selected for the bank survival equation align closely with existing work on the Great Depression (Calomiris and Mason, 2003; Das et al., 2022). A full list of the variables and their definitions is provided in Section 4.1.

The covariates in $\boldsymbol{x}_{i2}$ include many of the same measures as in $\boldsymbol{x}_{i1}$, but we include additional information on the number of acquisitions a bank was involved in between 1929 and 1934 as well as measures for the performance of nearby banks. We consider several definitions for nearby, including the town, county, and 10-mile radius. The covariates in $\boldsymbol{x}_{i3}$ also include acquisition information and measures for the performance of nearby banks in the years prior to a bank's exit.[2] In this way, the model setup is convenient because: (1) retaining separate outcome equations for the surviving and exiting samples allows us to construct these unique conditioning sets and extract more information with the covariate vectors, and (2) natural exclusion restrictions are available for each covariate vector because we condition on variables in different time periods.

For the vector of errors, we assume $\boldsymbol{\varepsilon}_i \equiv (\varepsilon_{i1}, \varepsilon_{i2}, \varepsilon_{i3}) \sim \mathcal{N}(0, \boldsymbol{\Omega})$, where

$$\boldsymbol{\Omega} = \begin{pmatrix} 1 & \omega_{12} & \omega_{13} \\ \omega_{12} & \omega_{22} & . \\ \omega_{13} & . & \omega_{33} \end{pmatrix}. \tag{6}$$

The unit restriction in the ω_{11} position is the usual normalization for identification in binary data models. Alternatively, ω_{33} is left as a free parameter and we meet the location and scaling restrictions for the ordered outcome with restrictions on the cutpoint parameters, which we detail in Section 2.2. The parameter ω_{23} is not identified because the second and third outcomes, bank exit type and risk changes, cannot be observed together.

Because of incidental truncation, we never observe a full system of three equations. Instead, we observe two different bivariate systems. In defining each system, we stack the matrix of covariates in seemingly unrelated regression form. Let $N_1 = \{i : y_{i1} = 1\}$ be the n_1 observations in the surviving bank sample and $N_2 = \{i : y_{i1} = 0\}$ be the n_2 observations in the exiting bank sample. For the surviving bank sample, $i \in N_1$, we have:

$$\boldsymbol{y}^*_{iS} = (y^*_{i1}, y^*_{i2})', \quad \boldsymbol{X}_{iS} = \begin{pmatrix} \boldsymbol{x}'_{i1} & 0 \\ 0 & \boldsymbol{x}'_{i2} \end{pmatrix}, \quad \boldsymbol{\varepsilon}_{iS} \equiv (\varepsilon_{i1}, \varepsilon_{i2}) \sim N(0, \boldsymbol{\Omega_S}), \quad \boldsymbol{\Omega}_S = \begin{pmatrix} 1 & \omega_{12} \\ \omega_{12} & \omega_{22} \end{pmatrix}. \tag{7}$$

For the exiting bank sample, $i \in N_2$, we have:

$$\boldsymbol{y}^*_{iE} = (y^*_{i1}, y^*_{i3})', \quad \boldsymbol{X}_{iE} = \begin{pmatrix} \boldsymbol{x}'_{i1} & 0 \\ 0 & \boldsymbol{x}'_{i3} \end{pmatrix}, \quad \boldsymbol{\varepsilon}_{iE} \equiv (\varepsilon_{i1}, \varepsilon_{i3}) \sim N(0, \boldsymbol{\Omega_E}), \quad \boldsymbol{\Omega}_E = \begin{pmatrix} 1 & \omega_{13} \\ \omega_{13} & \omega_{33} \end{pmatrix}. \tag{8}$$

Letting $\boldsymbol{\theta}$ be all model parameters, the complete-data likelihood is given by:

$$f(\boldsymbol{y}, \boldsymbol{y}^*|\boldsymbol{\theta}) \propto \left[\prod_{i \in N_1} f(\boldsymbol{y}^*_{iS}|\boldsymbol{\theta})\right] \left[\prod_{i \in N_2} f(\boldsymbol{y}^*_{iE}|\boldsymbol{\theta})\right]. \tag{9}$$

[2] We do not know the exact date for each bank exit, but we know the year of exit.

Following Chib (2007), the likelihood is defined in terms of the two subsets of the sample. The discrete outcome variables in the first and third equations of this model render the likelihood analytically intractable. Thus, we circumvent the intractability by deriving a simulation-based algorithm and proceeding with a Bayesian approach for estimation.

2.2 Estimation

We apply standard semi-conjugate priors, $\pi(\boldsymbol{\beta}, \boldsymbol{\Omega}) = \mathcal{N}(\boldsymbol{\beta} \,|\boldsymbol{\beta}_0, \mathbf{B}_0)\mathcal{IW}(\boldsymbol{\Omega}|\upsilon, \mathbf{Q})$, where $\mathcal{N}$ represents the normal distribution and $\mathcal{IW}$ represents the inverse-Wishart distribution. Combining the likelihood and priors leads to the complete-data posterior distribution,

$$\pi(\boldsymbol{\theta}, \boldsymbol{y}^{*}|\boldsymbol{y}) \propto \left[\prod_{i \in N_1} f(\boldsymbol{y}_{iS}^{*}|\boldsymbol{\theta})\right] \left[\prod_{i \in N_2} f(\boldsymbol{y}_{iE}^{*}|\boldsymbol{\theta})\right] \times \mathcal{N}(\boldsymbol{\beta} \,|\boldsymbol{\beta}_0, \mathbf{B}_0) \times \mathcal{IW}(\boldsymbol{\Omega}|\upsilon, \mathbf{Q}).$$

We develop a posterior simulator that is a 3-block collapsed Gibbs sampler with data augmentation. The Markov chain Monte Carlo approach is particularly attractive because evaluation of the likelihood can be avoided. Following Chib (2007), Chib et al. (2009), Li (2011), and Vossmeyer (2016), the algorithm does not require simulation of the missing outcomes or the joint distribution of the potential outcomes. Such an approach improves the mixing properties of the Markov chain, has lower storage costs, and is computationally more efficient. Below, we summarize the MCMC algorithm. The Appendix provides full details on the conditional distributions and updating equations. Step 1 updates our $\boldsymbol{\beta}$ parameters and step 2 updates $\boldsymbol{\Omega}$ in a 1-block, 4-step procedure. Steps 3 and 4 are the data augmentation steps for the binary outcome and steps 5 through 7 are the data augmentation steps for the 3 ordered categories (Tanner and Wong, 1987; Albert and Chib, 1993).

MCMC Estimation Algorithm:

1. Sample $\boldsymbol{\beta}$ from the distribution $\boldsymbol{\beta}|\boldsymbol{y}, \boldsymbol{y}^{*}, \boldsymbol{\Omega}$.
2. Sample $\boldsymbol{\Omega}$ from the distribution $\boldsymbol{\Omega}|\boldsymbol{y}, \boldsymbol{y}^{*}, \boldsymbol{\beta}$.
3. For $i \in N_1,$ sample y_{i1}^{*} from the distribution $y_{i1}^{*}|\boldsymbol{y}, \boldsymbol{\theta}, \boldsymbol{y}_2^{*}$.
4. For $i \in N_2,$ sample y_{i1}^{*} from the distribution $y_{i1}^{*}|\boldsymbol{y}, \boldsymbol{\theta}, \boldsymbol{y}_3^{*}$.
5. For $i : y_{i3} = 1,$ sample y_{i3}^{*} from the distribution $y_{i3}^{*}|\boldsymbol{y}, \boldsymbol{\theta}, \boldsymbol{y}_1^{*}$.

6. For $i : y_{i3} = 2,$ sample y^*_{i3} from the distribution $y^*_{i3}|\boldsymbol{y}, \boldsymbol{\theta}, \boldsymbol{y}^*_1$.

7. For $i : y_{i3} = 3,$ sample y^*_{i3} from the distribution $y^*_{i3}|\boldsymbol{y}, \boldsymbol{\theta}, \boldsymbol{y}^*_1$.

A few elements of this algorithm are worth highlighting. First, with a unit restriction in the variance-covariance matrix, oftentimes the Metropolis-Hastings algorithm is needed, which can complicate estimation. To circumvent this issue, we apply a change-of-variable transformation to the conditional distribution of the variance-covariance matrix, providing a full set of tractable conditionals from which the estimates of $\boldsymbol{\Omega}$ can be backed out (Chib et al., 2009). Second, in order to meet the scaling and location restrictions necessary for identification with ordered outcomes, we set $\gamma_1 = 0$ and $\gamma_2 = 1$, as defined in Equation (5). Fixing $\boldsymbol{\gamma}$ preserves the ordering of the cut-points and negates estimation of $\boldsymbol{\gamma}$ parameters because there are only two cut-points when there are three ordered outcomes (Jeliazkov et al., 2008). Third, because we meet the location and scaling restrictions through $\boldsymbol{\gamma}$, ω_{33} is a free estimable element. Thus, as a combination of the points above, we avoid needing two Metropolis-Hastings steps for $\boldsymbol{\Omega}$ and $\boldsymbol{\gamma}$ and instead have a full set of tractable conditional densities. The only adaptions due to the $\boldsymbol{\gamma}$ restrictions are the regions of truncation in steps 5 through 7. Thus, we have all of the conditional distributions and updating formulas for a full Gibbs sampler.

3 Data

3.1 Data Sources

In order to understand how the financial crisis of the early 1930s altered and redistributed risk, we examine changes to commercial banks and trusts that occurred between July 1929 and July 1934 – in other words, just prior to the start of the Great Depression until after the conclusion of the banking crisis. Balance sheet information and network connections for all commercial banks as well as information on other bank-specific characteristics (location, Federal Reserve membership, routing number, etc.) are from the Rand McNally *Bankers Directory* (July 1929, July 1934). The July 1929 data are described in further detail in Das et al. (2022). We add to these data by merging into them balance sheet and network data for every bank in July 1934, allowing us to track changes for individual banks over the financial crisis of the early 1930s.

We augment these data with new hand-collected information on all mergers, acquisitions, and failures using a list of discontinued financial institutions also published by Rand McNally.[3] Given the sheer size of the American commercial banking system (more than 24,000 institutions in 1929) and the number of mergers, acquisitions, and failures during our sample period, a key contribution of this paper is to use these data to track the resolution of each of these events through our sample period. Banks are matched between 1929 and 1934 using their name, location, and routing number, i.e., a unique bank identification number. Additionally, the discontinued list details all name and location changes between 1929 and 1934, so we are able to follow the fate of individual banks over time. To the best of our knowledge, our dataset is the first to track every commercial bank's outcome for the Great Depression in sufficient detail such that a researcher can then identify how individual bank-level events altered firm-specific and aggregate risk and which banks acquire. Lastly, we merge county-level data from the 1930 census of population, manufacturing, and agriculture to control for a bank's business environment.

3.2 Definitions

We begin by describing how banks in our sample fit into the subgroups of our model (Figure 1). First, banks in the surviving sample appear and have balance sheet data in both the 1929 and 1934 issues of the Rand McNally *Bankers Directory.* Second, banks in the exiting sample are banks that appear and have balance sheet data in the 1929 Rand McNally *Bankers Directory* but do not appear in 1934. Instead, these banks appear in Rand McNally's "Discontinued List."

Third, we use the discontinued list to classify exiting banks into three ordered categories. When the discontinued list states that a bank "merged with" or "consolidated with" another bank, we define that as a Consolidation. When the discontinued list states that a bank was "absorbed by," "purchased by," or "taken over by" another bank, we define that as a bank being Absorbed. This outcome is more like a merger under duress, similar to a purchase and assumption agreement under today's FDIC. Bankers of the era we study viewed absorptions as a means of "survival" and contemporary policymakers viewed it as "the only permanent solution where the overbanked condition exists" (FRC, 1931, p.64). These two outcomes – consolidations and absorptions – are

[3]The published list in Rand McNally is called "Discontinued Bank Titles" and is organized alphabetically by state and city. A typical example of an entry would be "Alabama, Jacksonville, Alabama Trust & Savings Bank discontinued 1931" (1934, p.2037) or "Alabama, Mobile, The Mobile National Bank acquired by Merchants National Bank 1931" (1934, p.2037).

merger-related outcomes where two or more banks are involved in a union under a single charter (FRB, 1937, p.1085).[4] Consolidation is a "better" outcome than absorbed, but absorbed is a better outcome than failure. Consolidation is ordered higher since mergers of this type were quite flexible. Subject to the approval of shareholders of both existing banks, the typical merged banking enterprise only had to report simple information, such as name and place of business, the number of directors, the shares of new stock issued, capital, surplus, and profits, and any assets that were being eliminated (see FRB (1931) for a review of federal and state laws on consolidations and mergers). By contrast, an absorption required one bank to purchase the assets and assume the liabilities of the liquidating bank (White, 1985), a process that could potentially be more time-consuming given creditor claims on distressed banks' assets and shareholder liability.

When the discontinued list states that a bank was "discontinued" and no other bank was involved, we define that as a <u>Failure</u>.[5] The latent variable y_{i3}^* in Equation (5) underlies the three ordered categories of Consolidation, Absorbed, and Failure. One way to think about this continuous latent utility is that it represents the remaining resources of bank i in the system, where consolidation would preserve the most resources and failure would preserve the least.[6]

Between 1929 and 1934, more than 9,000 banks closed. Bank consolidations and absorptions were subject to review and consent of regulators, but the applicable federal and state statutes indicate that this process was largely pro forma – meant to ensure that the surviving entity was solvent at the time of the merger and that the transaction was not defrauding creditors. Regulators could recommend that troubled institutions seek merger partners, but they did not facilitate mergers (Koch et al., 2023). In other words, bank mergers during our sample period were not evaluated for their effects on competition, as they are today, or for financial-stability considerations.[7] In this regard, our analysis provides a benchmark for comparing periods where bank merger and acquisition

[4] Banks that are converted into branches, either through absorption or consolidation are included in our sample.

[5] We include voluntary liquidations with the group of failures. In theory, this category should include only solvent banks that shut down operations, but as the Federal Reserve discusses, during crisis periods, some instances of voluntary liquidation may have included losses to depositors (FRC, 1931, p.60). However, our analysis is robust to omitting this group from the failure sample, as the Discontinued List clearly states voluntary liquidations separate from discontinued banks. There are 295 banks that exit our sample through voluntary liquidations.

[6] A multinomial choice model approach for the type of bank exit would not be appropriate because many failing banks did not have a "choice" to merge and therefore that cannot be represented as a choice alternative in the specification.

[7] Indeed, the Clayton Act was not amended to prevent anti-competitive mergers among banks until 1950. The U.S. Supreme Court first considered applying federal antitrust laws to banks in 1963 (United States v. Philadelphia Nat'l Bank, 374 U.S. 321), subsequent to the passage of the Bank Merger Act of 1960, which directed bank regulators to consider competitive factors before approving mergers.

(M&A) activity faces potentially greater scrutiny.

A final important definition is that of Acquirer, which is the dominant bank in a merger. Acquirer is one of our key covariates as we investigate how merger activity influences changes to balance sheet and systemic risk. With these definitions, we have our outcomes for Equation 1 (surviving and exiting) and Equation 3 (consolidation, absorbed, and failure). The outcome for Equation 2 is described in the next sections.

3.3 Balance-Sheet Risk

We develop two measures of changes in individual bank risk (Equation 2's outcome): (1) balance-sheet risk and (2) systemic risk. We first describe the balance-sheet-risk measure and examine how it changed between 1929 and 1934.

In developing a measure for balance-sheet risk, it is important to recognize that, in considering the entire population of U.S. commercial banks, we are limited to the historical balance-sheet data available in the *Bankers Directory*, which lists four categories on the asset side (cash and exchanges, bonds and securities, loans and discounts, and miscellaneous) and four categories on the liabilities side (deposits, surplus and profits, paid-up capital, and other). While more granular data exist for the subset of banks that are national banks or Federal Reserve members, that is the minority of the banking population: more than 70% of bank exits were nonmember institutions. Thus, we employ the balance sheet data available in the *Bankers Directory* to study the entire banking population.

Balance-sheet risk is calculated as a leverage-adjusted measure of inverse profitability. The measure was developed in Das et al. (2022), where further details are available. Specifically, we construct a composite measure of credit risk (R), which is the product of inverse profitability (C) and transformed leverage (L):

$$R = C \times L \tag{10}$$

$$C = a + \frac{1}{1 + BUF} \cdot b \tag{11}$$

$$L = \ln(1 + Assets/Equity). \tag{12}$$

BUF is a buffer stock of retained earnings, defined as surplus and profits divided by equity (the sum of surplus and profits and paid-up capital). Banks considered BUF to expand operations or write off losses relative to the book value of net worth in the 1920s and 1930s (Carlson and Rose, 2015). Because BUF is bounded between 0 and 1, we set the scalars $a = -8$ and $b = 18$ so that C

is then confined to a value between 1 and 10, and may be thought of as a mapping into a rating, with values inversely proportional to quality. We multiply C by a transformed measure of leverage L, where $Assets$ is the sum of loans and discounts, miscellaneous assets, bonds and securities, and cash and exchanges. Our measure, R, is as close as we can get to an inverse distance-to-default, analogous to credit risk in the Merton (1974) model. Das et al. (2022) demonstrate the superior performance of R in predicting the probability of bank closure relative to other balance sheet measures. Additionally, Das et al. (2022) show that, even with modern institutions and recent data, R most closely aligns with credit ratings.

Table 1 presents summary statistics of R in 1929 and 1934. Based on 1929 values of R, banks that exited the system had higher balance-sheet risk than those that survived. This result confirms a basic finding in other studies on banking distress: balance sheets are accurate predictors of insolvency (Calomiris and Mason, 2003). Despite the exit of ex-ante "weak" banks from the system, the table also shows that average balance-sheet risk in the system was not purged. In 1934, after the crisis had subsided, it was 10% higher than its pre-crisis value. More specifically, for the sample of 15,039 surviving banks that appear in both 1929 and 1934, their average R increased from 9.7 to 10.7.[8] The change in R from 1929 to 1934 is our first outcome for Equation 2.

Table 1: Averages of balance sheet risk (R) for subgroups of banks in 1929 and 1934.

Measure	1929 All Banks	1929 Surviving	1929 Exiting	1934
R mean	10.5	9.7	11.8	10.7
R std. dev.	(4.3)	(4.1)	(4.2)	(4.2)
Number of Banks	24,305	15,039	9,266	15,039

3.4 Systemic Risk

We also analyze a bank's contribution to systemic risk, which arises from its default risk as well as its position in the financial system. In other words, banks may be risky because they are well-connected and positioned centrally within a banking system or because they have characteristics that make them more susceptible to failure. R is our proxy for a bank's default risk. To measure a bank's position in the network, we utilize information on correspondent relationships, which are

[8] With our data source, we don't have a way of knowing what losses are being written down as a result of the crisis. However, building R from the equity side alleviates some of these concerns.

stated (and therefore observable) contractual relationships between banks. Since Rand McNally provides information on all correspondents of commercial banks, this allows us to avoid having to generate hypothetical linkages through data-inference methods. Commercial banks relied on their correspondents to obtain and deliver services in distant locations. A primary reason banks formed these linkages was so that they could deposit funds in other banks, on behalf of their customers or for their own use (interbank deposits). Details on the correspondent network for our sample period, its network properties, and of the systemic risk measures we employ are described in Das et al. (2022).

We construct the network adjacency matrix, A, for the entire banking system in 1929 and 1934. The matrix is defined as $A(i, j)$, $i, j = 1, 2, ..., n$, where n is the total number of banks or nodes in the system. $A(i, j) = 1$ if respondent bank i holds interbank deposits with correspondent bank j, else $A(i, j) = 0$. These interbank deposits were recorded on bank balance sheets as either "due to" or "due from," representing the directional nature of the relationship. Therefore, A is not a symmetric matrix. In 1929, A has 70,679 network connections. After the crisis, in 1934, there are 41,313 connections. The mean number of correspondents per bank is between 2 and 3, with a slight decrease between 1929 and 1934. In both periods, the network has a pyramid-shape topology, reflecting the correspondent network's concentration in what were known as reserve and central reserve cities, and the degree distribution follows a power law.

Following and extending the metrics in Das (2016) and Das et al. (2019), systemic risk *per bank*, S, is defined as:

$$\begin{aligned} S &= \frac{1}{n} \cdot \sqrt{R' \cdot A \cdot R} \\ &= \sqrt{\frac{R'}{n} \cdot A \cdot \frac{R}{n}} \\ &= \sqrt{Q' \cdot A \cdot Q}. \end{aligned} \tag{13}$$

Using the R vector (balance sheet risk) and A matrix (correspondent network risk) for 1929 and 1934, the output from Equation (13) is a single value for systemic risk in each year. An advantage of this measure is that it can be decomposed bank by bank as follows:

$$S = \frac{\partial S}{\partial Q_1} \cdot Q_1 + \frac{\partial S}{\partial Q_2} \cdot Q_2 + \ldots + \frac{\partial S}{\partial Q_n} \cdot Q_n \tag{14}$$

where

$$\frac{\partial S}{\partial Q} = \frac{1}{2S}[A \cdot Q + A' \cdot Q] \in \mathcal{R}^n. \quad (15)$$

This formulation allows us to compute each bank's contribution to systemic risk where we have already normalized for the number of banks in the system. We do this computation for both 1929 and 1934 samples to understand how systemic risk changed over time.[9] The change in a bank's contribution to systemic risk is our second outcome variable for Equation (2).

Table 2 presents summary statistics of our systemic risk measure. The first row shows that overall systemic risk rose by 33% as a result of the crisis. When looking at bank-level contributions to systemic risk (i.e., $\frac{\partial S}{\partial Q_i} \cdot Q_i$), exiting banks were less systemically risky than surviving banks in 1929 (0.034 vs. 0.046). Generally, banks that survived the Great Depression were larger and carried more network importance (Calomiris et al., 2022). Notably, banks that survived the early 1930s experienced a large increase in average contributions to systemic risk. While more systemically risky banks, on average, survived, they also took on substantially more risk. Thus, neither the average balance-sheet risk nor the systemic risk measures support the idea that risk was cleansed from the system by the massive banking crisis of the early 1930s. Whether and how the risk was redistributed to surviving banks is the core question our research addresses.

Table 2: Summary statistics of our systemic risk measure for subgroups of banks in 1929 and 1934.

Measure	1929 All Banks	1929 Surviving	1929 Exiting	1934
Systemic risk, S	1,040	.	.	1,380
Bank-level systemic risk (avg)	0.041	0.046	0.034	0.085
Bank-level systemic risk (std dev)	(4.3)	(4.1)	(4.2)	(4.2)
Number of Banks	24,305	15,039	9,266	15,039

Note: The systemic risk values are multiplied by 10,000 for numerical precision.

3.5 Descriptive Statistics

As briefly described earlier, the crisis of the early 1930s was severe. Only 62% of the approximately 24,000 commercial banks that existed in 1929 survived our sample period. The remainder of banks exited the system. Of the 9,266 exits, 66% were failures, 17% were absorptions, and 17% were

[9] This measure of systemic risk is the only fitting measure for this time period when considering all banks in the system. Systemic risk measures constructed from stock price co-movements would not work because few banks were publicly-listed companies.

consolidations. Thus, as is true of many financial crises (Wheelock, 2011), the early 1930s were characterized by heightened industry consolidation. More than 3,000 bank mergers and acquisitions (M&As) occurred.

The columns of Table 3 decompose the 1929 population of banks by their 1934 survival status, showing 1929 mean values of size, risk, and other bank attributes. As would be expected, on average, the 15,039 surviving banks ex ante had lower balance-sheet risk, more assets, and were more likely to be members of the Federal Reserve System than either banks that failed or those involved in M&A. Interestingly, as we look across our ordered subgroups of banks, these numbers gradually change. For instance, assets are largest for survivors, followed in order by consolidations, absorptions, and failures. This gradual movement through the groups motivates our ordered outcome in Equation (3). Even among the merger outcomes, banks in the consolidation group look quite different from those in the absorbed group.

Table 3: 1929 averages of bank subgroups.

Variable	**Survive**	**Consolidate**	**Absorbed**	**Failure**
Number of Banks	15,039	1,552	1,556	6,158
Risk, R	9.71	11.20	11.50	12.11
Systemic Risk Contribution	0.046	0.046	0.046	0.028
Assets (ln)	13.52	13.49	13.07	12.87
Fed Member (share)	0.38	0.37	0.35	0.23

Turning to a primary research question of whether bank acquisitions altered risk, Table 4 presents summary statistics for surviving banks. The statistics show the average change in balance-sheet characteristics for banks that acquired zero banks, one bank, two banks, or three or more banks. The table demonstrates that, of the 15,039 surviving banks, 1,346 banks acquired one bank (last column of row 2). These acquirers experienced an average increase in R of 1.61 and S of 0.0512. Further, if a bank made an acquisition, no matter how many banks it acquired, its balance-sheet and systemic risk were higher (comparing rows 2-4 to the baseline of no acquisitions shown in row 1). Moreover, systemic risk and balance sheet risk monotonically increase with the number of banks acquired. Those banks acquiring three or more banks exhibit more than three times the balance-sheet risk and twenty-seven times the systemic risk of banks that did not acquire a bank. Overall, about 10% of surviving banks made an acquisition – a fairly large sample of banks – and the changes displayed in the table demonstrate acquisitions as a risk-spreading channel.

Table 4 also shows changes to total assets, degree, C, and L. On average, during our sample period, assets were falling for banks; however, those that acquired more than one bank experienced an increase in total assets. And, on average, interbank network connectivity (degree) fell, with larger changes occurring for acquiring institutions. Further, banks began to deleverage by reducing their holdings of loans and investments (corporate bonds) in response to the panics of the early 1930s and the ongoing Great Depression. However, for banks making acquisitions, deleveraging occurred to much less of a degree, as shown in the $\triangle L$ column of the table. Indeed, as more banks were acquired, average leverage declined very little.

Table 4: Average changes for surviving banks based on the number of acquisitions.

# Banks Acquired	**ΔRisk**	**ΔSysRisk**	**ΔAssets**	**ΔLoans**	**ΔDegree**	**ΔC**	**ΔL**	**Obs.**
0	0.92	0.0311	-0.308	-0.636	-1.62	1.04	-0.21	13,463
1	1.61	0.0512	-0.109	-0.454	-1.69	1.06	-0.12	1,346
2	2.35	0.0863	0.059	-0.336	-4.14	1.24	-0.06	173
≥3	3.13	0.8596	0.208	-0.226	-18.91	1.42	-0.01	57
All Surviving Banks	1.00	0.0366	-0.282	-0.615	-1.72	1.04	-0.20	15,039

Bank size provides an additional dimension to explore changes in systemic risk because the largest banks are often the most connected and systemically risky. In addition, in the modern banking system, acquisitions involving large institutions are often viewed by policymakers as an immediate way to improve financial stability, regardless of their effects on risk after the crisis subsides. The left panel of Figure 2 therefore presents the total contributions to changes in systemic risk for the largest 10, 50, 100, and more banks, where size is determined by total assets in 1929. The right panel displays the share of banks in each sample subgroup that were acquirers. Because these statistics focus on the change in S, the sample is restricted to surviving banks. The figure shows that of the largest 10 banks, five of them were acquirers and those five banks contributed almost five times more to increased systemic risk than non-acquiring "mega banks." These five acquiring banks contributed 4% to the total change in systemic risk (out of over 15,000 banks). If every bank contributed equally to systemic risk, that would imply these five banks would have only contributed 0.033%. In other words, their contribution to risk was substantial, more than 120 times greater than if the distribution were uniform. When we expand our lens and consider the largest 100 banks, non-acquirers (67 banks) actually reduced systemic risk by 2%, whereas acquiring banks (33 banks) increased it by 8%. When we consider the entire size distribution, the share of acquirers falls. As also shown in the figure, acquirers made up about 10% of surviving banks and they accounted for about a quarter of the overall increase in systemic risk.

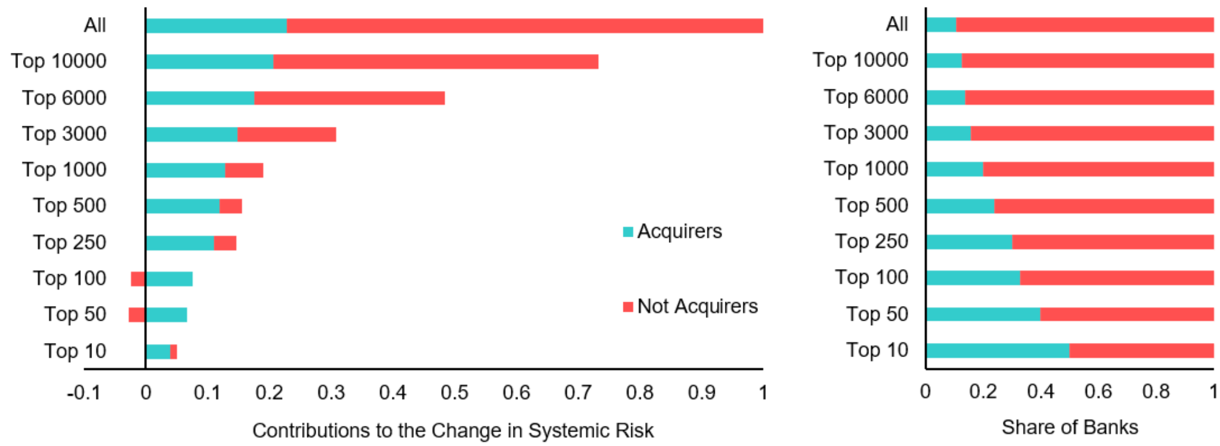

Figure 2: The left panel displays contributions to the change in systemic risk for banks that made acquisitions and those that do not do so. The statistics are presented for subgroups based on bank size (1929 total assets). The right panel displays the share of banks in those subgroups that were acquirers.

The left panel of Figure 3 presents the location of all surviving (blue) and exiting (red) banks. The right panel presents the location of all merger activity, where exiting banks are in red and acquiring banks are in blue. The size of the blue dot represents the number of acquisitions, where a larger dot implies more acquisitions. For the most part, one cannot disentangle the red and blue dots in the right panel because over 66% of acquiring-exit bank pairs were in the same town. Note that particular regions, like California, show a large number of acquisitions by a particular bank. This is typically a feature of states that permitted branching (there was no nationwide branching during our sample period). In these instances, the exiting bank was absorbed and became a branch of a larger headquarter bank, usually located in a larger city. For instance, many struggling banks in small towns in California became branches of the Bank of America, which had its headquarters in San Francisco. On average, in the acquiring-exiting pairs, relative to the acquiring bank, the exiting bank was smaller, carried more balance-sheet risk, and was less likely to be a Federal Reserve member. In comparing the left and right panels of Figure 3, it is important to note that merger activity was widespread and not concentrated in a particular region of the United States. Our econometric model accommodates spatial correlation in bank resolutions.

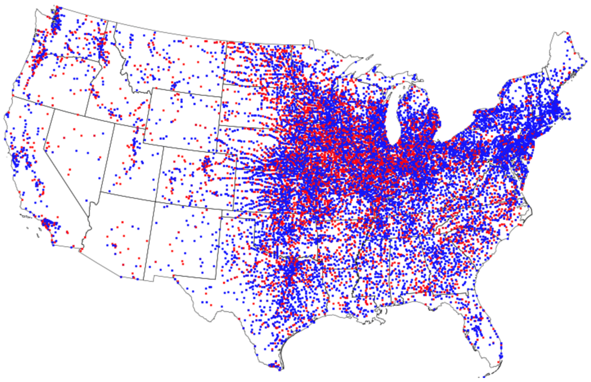

Figure 3: The left panel displays the location of all bank survivals (blue) and exits (red). The right panel displays merger activity with all acquirer (blue) and exiting (red) bank pairs. The size of the blue dot represents the number of acquisitions.

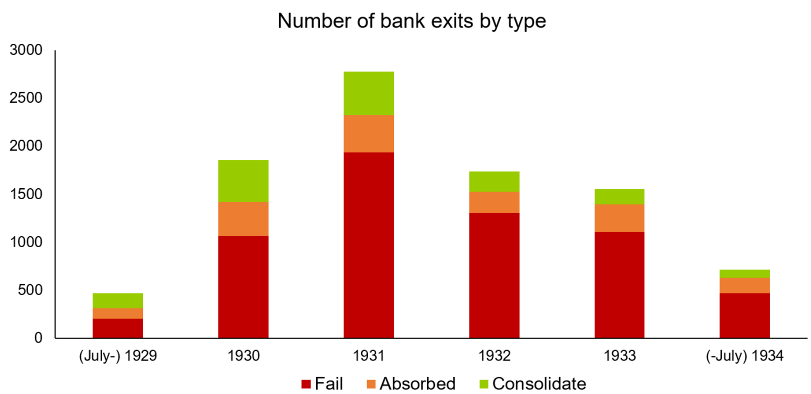

Figure 4: The number of bank exits by type from 1929 to 1934.

Lastly, Figure 4 is a stacked bar graph displaying the annual number of exits due to failure, absorption, or consolidation. Exits peaked in 1931 and merger activity occurred throughout the worst years of the Great Depression. One may worry that mergers only occurred early on, and once pairings were complete, there would be few conjoins. However, for the distress occurring in the early 1930s, Figure 4 shows that this does not appear to be the case. Nevertheless, our econometric model accommodates serial correlation in bank outcomes.

4 Results

4.1 Preliminaries

We estimate our trivariate model using the MCMC algorithm. The priors on $\boldsymbol{\beta}$ are centered at 0 with a variance of 10. The results are based on 11,000 MCMC draws with a burn-in of 1,000 draws. The model and estimation performed well. Inefficiency factors are low, suggesting a good mixing of the Markov chain and no need for tapering the chain. Additionally, we find the results are not sensitive to the hyperparameters on the prior distribution, as we explored training sample priors, higher variances, and lower variances.

Table 5 defines the variables that enter the model. We have a large set of bank-level controls measured in 1929, including balance-sheet characteristics, a bank's local market share used to proxy for competition (measured by a bank's share of county-level deposits), its network importance, and its risk emanating from network connections (i.e., network neighbors). We also have bank-specific controls that capture acquisitions and nearby bank outcomes that occurred between 1929 and 1934 as well as a variety of variables that capture differences in county characteristics and regulation.[10] We also include year indicators in Equation (3) to capture any aggregate macroeconomic changes that would impact bank exits.

4.2 Estimates

Table 6 displays the results of the model where we consider the two risk measures, R (Model 1) and S (Model 2). Columns [2] and [3] are the results for Equations (2) and (3), respectively, when the outcome for Equation (2) is the change in balance-sheet risk. Columns [4] and [5] are the results for Equations (2) and (3), respectively, when the outcome for Equation (2) is the change in systemic risk. Because the findings from Equation (1) align with the results in Das et al. (2022) and the broader literature on bank survival in the Great Depression, results for Equation (1) are suppressed. The novel contribution of our research lies in the estimates for Equations (2) and (3).

In examining the results for Equation (2), recall that the model has conditioned on the selection mechanism of being in the surviving bank sample. We find that the number of acquisitions had a positive and significant effect on the change in balance-sheet risk and systemic risk. From Tables 1

[10] We consider three definitions of "nearby" – the town, the county, and a 10-mile radius. The results shown in the table use the 10-mile radius variables, but the results are not materially different using the alternative town or county definitions.

Table 5: Definitions of the variables.

Variable	Definition
Loans/Assets	Ratio of loans and discounts to total assets
Bonds/Assets	Ratio of bonds and securities to total assets
LnAssets	Ln(Total Assets)
Fed Member	Indicator for Federal Reserve membership
Central Reserve City	Indicator for central reserve city location
Reserve City	Indicator for reserve city location
LnPopulation	Ln(County Population)
Manufacturing per capita	Manufacturing establishments in the county divided by county population†
Cropland per capita	Acreage of cropland in the county divided by county population
Branch Intensity	# of banks operating branches in the state / total number of banks in the state
Num Banks in County	Number of banks operating in the county†
Deposits/County Deposits	Ratio of deposits held at the bank to the sum of all bank deposits in the county
R	Balance sheet risk measure
Network Neighbor in-R	The sum of balance-sheet risk from network neighbors with inward links
Network Neighbor out-R	The sum of balance-sheet risk from network neighbors with outward links
County-R	The sum of balance-sheet risk from banks in the same county
EigenCent	Eigenvector centrality, C
SysRisk Percent	Percent contribution to systemic risk (S)
Nearby Acquirers	Number of potential acquirer banks nearby
Number Acquired	Number of banks acquired
Nearby Prior Fail	Number of nearby banks that failed in the years prior to exit
Nearby Prior Absorption	Number of nearby banks that were absorbed in the years prior to exit
Nearby Prior Consolidation	Number of nearby banks that consolidated in the years prior to exit
Nearby Failure Fraction	Fraction of nearby banks that failed between 1929 and 1934
Fed District FE	Indicators for the 12 Federal Reserve Districts
Exit Year FE	Indicators for the years 1929 to 1934

Note: County population, manufacturing establishments, and acres of cropland are from the 1930 *U.S. Censuses of Population, Manufacturing, and Agriculture*. † "Manufacturing per capita" is multiplied by 100 to rescale for numerical precision. "Num Banks in County" is divided by 10; and "Network Neighbor in-R," "Network Neighbor out-R," and "County-R" are transformed by square roots.

and 2, the average change in balance-sheet risk was 1.0 and the average change in systemic risk was about 0.04. Thus, the magnitudes of 0.256 and 0.013 for *Number Acquired* shown in Columns [2] and [4] of the table are economically meaningful and represent about a quarter of the overall change in risk for surviving banks between 1929 and 1934. With each additional acquisition, a bank's balance-sheet risk and contribution to systemic risk increased, consistent with the raw data demonstrated in Table 4. These results suggest that risk is transferred from struggling, exiting banks to healthier, surviving banks through the merger process, thus enabling risk to remain in the financial system.

Other factors also influenced changes to bank risk. The fraction of nearby bank failures and Fed membership positively affected balance-sheet risk but not systemic risk (Columns [2] and [4],

Table 6: Estimating Changes to Balance Sheet Risk and Systemic Risk

	Model 1 Balance Sheet Risk		Model 2 Systemic Risk	
[1]	**[2]**	**[3]**	**[4]**	**[5]**
Variable	**Eq2: ΔRisk**	**Eq3: Ordered**	**Eq2: ΔSysRisk**	**Eq3: Ordered**
Intercept	0.894 (0.637)	0.378 (0.541)	-0.030 (0.033)	-0.744 (0.490)
Number Acquired	0.256 (0.038)	-1.704 (0.171)	0.013 (0.001)	-1.774 (0.192)
Nearby Failure Fraction	0.574 (0.158)		0.004 (0.004)	
Nearby Acquirers		0.207 (0.016)		0.189 (0.013)
Nearby Prior Fail		0.001 (0.005)		-0.003 (0.006)
Nearby Prior Absorption		-0.019 (0.022)		-0.022 (0.022)
Nearby Prior Consol		-0.160 (0.018)		-0.141 (0.015)
$(\text{Loans/Assets})_{29}$	0.506 (0.339)	-0.658 (0.249)	0.021 (0.017)	-0.451 (0.224)
$(\text{Bonds/Assets})_{29}$	2.447 (0.354)	2.131 (0.323)	0.124 (0.018)	0.929 (0.249)
$ln(Assets_{29})$	0.366 (0.035)	0.418 (0.047)	0.006 (0.002)	0.157 (0.026)
R_{29}	-0.642 (0.009)	-0.102 (0.011)	-0.006 (0.000)	-0.037 (0.006)
$\text{SysRisk Percent}_{29}$	1.526 (0.951)	2.281 (1.112)	1.187 (0.082)	0.325 (2.223)
Fed Member	1.490 (0.077)	0.351 (0.061)	0.004 (0.004)	0.311 (0.056)
Central Reserve City	-3.353 (0.427)	-0.478 (0.340)	-0.136 (0.020)	-0.498 (0.278)
Reserve City	-1.216 (0.180)	-0.411 (0.143)	-0.066 (0.009)	-0.030 (0.119)
LnPopulation	-0.401 (0.039)	-0.304 (0.040)	-0.012 (0.002)	-0.124 (0.028)
Manufacturing per capita	1.171 (0.436)	2.060 (0.335)	-0.103 (0.021)	1.614 (0.303)
Cropland per capita	-0.031 (0.005)	-0.015 (0.004)	0.000 (0.000)	-0.010 (0.003)
Branch Intensity	3.288 (0.748)	1.542 (0.669)	0.114 (0.040)	0.964 (0.605)
EigenCent_{29}	3.777 (2.000)	-0.335 (2.050)	5.357 (0.261)	0.245 (2.069)
Fed District FE	Yes	Yes	Yes	Yes
Exit Year FE	.	Yes	.	Yes
Eq1 Full Controls	Yes	Yes	Yes	Yes

This table contains Equation (2) and Equation (3) results from two models. Posterior means and standard deviations (in parentheses) are presented. The difference between the two models is the outcome for Equation (2), where we explore the change in balance-sheet risk then the change in systemic risk. Equation (1) results are not presented. Equation (1) controls include: loans/assets, bonds/assets, lnassets, Fed member, central reserve city, reserve city, LnPopulation, Manufacturing per capita, Cropland per capita, branch intensity, number of banks in county, share of deposits relative to the county, R, SysRisk percent, sum of network neighbor out-link R, sum of network neighbor in-link R, sum of county R, eigenvector centrality, and Federal Reserve district indicators.

respectively). Nearby failures indicate local distress mattered for the Great Depression, perhaps induced by panic, falling crop prices, or other shocks. These events may have directly impacted a bank's balance sheet and only indirectly impacted the correspondent network (unless there was a correspondent-respondent linkage with the failing bank). Acquisitions, on the other hand, could have directly impacted the balance sheet of central nodes in the network. Additionally, we find that bank size had a positive effect on both forms of risk. Prior to the start of the banking panics in 1929, larger banks had less balance-sheet risk and more network importance than smaller banks. As their balance sheets grew riskier thereafter, central nodes in the correspondent network became riskier, thus influencing systemic risk. Even though the total network connections shrank by 40% (as did the number of nodes), the topology of the network changed very little, i.e., the degree distribution did not dramatically change between 1929 and 1934. Thus, increased systemic risk was not due to changes in network density, but instead due to the concentration of risk at more central nodes. In Section 4.3, we confirm this by considering changes to network connectivity for surviving banks.

The results for Equation (3) shown in Columns [3] and [5] shed light on factors influencing exit probability via merger. Note that a positive estimate implies an increased probability of exiting through a merger and a negative estimate implies a heightened probability of exiting through a failure. Again, the model has conditioned on the selection mechanism of being in the exiting bank sample. Columns [3] and [5] show that the number of acquisitions is negatively associated with the probability of merger, implying that in the years before a bank's exit, if a bank acquired other institutions, it decreased the probability of exiting through a merger (i.e., getting acquired themselves). Because the results from Equation (2) suggest that acquiring a bank increased balance-sheet risk, doing so could have led to a less attractive balance sheet when that bank was then being targeted for potential acquisition. It is worth noting that the failure rate of acquiring banks was 15%, much lower than the unconditional probability of failure in the sample (25%).

Additionally, we find that the outcomes of nearby banks influence the exit type of remaining banks. Specifically, the number of nearby consolidations is negatively associated with merger outcomes. Thus, in the years prior to a bank's exit, if nearby banks exited through consolidation, it subsequently increased the probability of exiting through a failure. Perhaps nearby consolidations imply banks had already paired off, leaving few merger partners nearby. Federal Reserve membership, on the other hand, increased the probability of exiting through a merger.

The results for Equation (3) thus provide evidence that exit type is influenced by the outcomes of nearby banks in previous years, demonstrating the strong spatial and serial dependence in bank outcomes. Such dependence is conveniently captured in our joint model. Without the separate potential outcome equations for surviving and exiting banks, one could not specify covariates constructed as a function of the "years prior to exit" as that would be unobserved for surviving banks. In our model, we are able to specify unique conditioning sets tailored to banks either surviving or exiting. The joint model also estimates four parameters in the variance-covariance matrix, including the covariance between the errors of the survival equation and changes to risk equation and the survival equation and exit-type equation. Equation (16) presents the implied correlation from our estimates of the variance-covariance matrix.

$$\hat{\mathbf{\Omega}}_{corr} = \begin{pmatrix} 1 & 0.90 & 0.95 \\ 0.90 & 1 & \cdot \\ 0.95 & \cdot & 1 \end{pmatrix} \tag{16}$$

The estimates are large, positive, and statistically different from 0, meaning that ignoring selection and correlation in the unobservables can lead to nontrivial biases in the estimates. To explore the size and direction of bias, we treat Equation (2) as a simple linear model and estimate it by ordinary least squares. The result for the number of acquisitions is about 50% higher in the univariate model, suggesting a larger channel for risk spreading. The OLS results generally agree with the direction and significance of the findings, but the magnitudes overestimate the influence of acquisitions.

4.3 Additional Considerations

4.3.1 Nonlinearities

The main covariate of interest in our trivariate model is the number of acquisitions. Table 4 suggests that each additional acquisition may have had a nonlinear effect on changes in risk. To investigate this possibility, we consider a specification where we model acquisitions in bins as opposed to a count. That is, instead of *Number Acquired* as a variable in Equations (2) and (3), we include mutually exclusive and exhaustive indicators for 1 acquisition, 2 acquisitions, and 3 or more acquisitions. The coefficients on these indicator variables are thus expressed relative to no acquisitions. Other than this change, the model is identical to the specification in Table 6. The results for the new variables are displayed in Table 7.

Table 7: Estimation Results for Indicators of Acquisitions

	Model 1 Balance Sheet Risk		Model 2 Systemic Risk	
[1]	**[2]**	**[3]**	**[4]**	**[5]**
Variable	**Eq2: ΔRisk**	**Eq3: Ordered**	**Eq2: ΔSysRisk**	**Eq3: Ordered**
1 Bank Acquired	0.697 (0.094)	-2.017 (0.186)	0.008 (0.003)	-2.234 (0.259)
2 Banks Acquired	0.912 (0.259)	-2.400 (0.641)	0.017 (0.007)	-2.403 (0.720)
≥3 Banks Acquired	1.647 (0.428)	-2.367 (0.801)	0.098 (0.009)	-2.528 (0.943)

This table contains Equation (2) and Equation (3) results from two models. Posterior means and standard deviations (in parentheses) are presented. The difference between the two models is the outcome for Equation (2), where we explore the change in balance sheet risk then the change in systemic risk. Equation (1) results are not presented. The model specification is identical to Table 6 except for the acquisition variable.

The estimates shown in the table demonstrate how additional bank acquisitions altered risk during the early 1930s. Each additional acquisition increased both balance-sheet and systemic risk. Relative to surviving banks that did not make acquisitions, banks that acquired one bank had a change in R that was 0.697 higher. When we compare these estimates to the changes shown in the sample summary statistics (Table 4), it appears that changes in risk are almost entirely explained by the acquisitions themselves, as opposed to unobservables driving the acquisition choice. These results are consistent with the broader literature on corporate mergers, which has found an increased risk of default for the acquiring firm (Furfine and Rosen, 2011). Relative to surviving banks that did not make acquisitions, banks that acquired three or more banks contributed 0.098 more to systemic risk. Institutions that acquired three or more banks were very large in size, thus these econometric results align with Figure 2, demonstrating that the greatest contributors to systemic risk are the largest acquiring banks. Table 7 also shows that, for banks that exited the system (Equation 3 results), prior acquisitions reduced the probability of exiting through a merger. This effect is larger (in absolute value) as the number of acquisitions increases.

4.3.2 Size Sub-samples

It is important to note that acquisitions during the Depression occurred across the size distribution of banks, as shown in Figure 2. That said, mergers between large banks are a prominent feature of recent crises and banking turmoil as are policymakers' concerns about implicit backstopping ("too big to fail" (TBTF) policies). As such, there is considerable interest in understanding how mergers and acquisitions involving large institutions affect risk. To shed light on this issue, we additionally examine results based on bank size. We divide our sample into quintiles, based on total assets in 1929. We estimate the model in Table 6 but restrict our sample to each of the five quintiles.

Table 8 focuses on the results for our main covariate of interest, *Number Acquired*, both in the balance-sheet-risk model and systemic-risk model. We find positive effects that are statistically different from zero in all five samples and in both models, emphasizing that our results are not driven by a particular quintile. Interestingly, the effect of acquisitions on changes to balance sheet risk is largest when the sample is restricted to the smallest quintile. Smaller banks usually have less diversified portfolios (Demsetz and Strahan, 1997); therefore, acquiring a troubled institution may have had a larger effect on their less-buffered balance sheets. Additionally, we find that the effect of acquisitions on changes to systemic risk is greatest when the sample is restricted to the largest size quintile. This result reflects the fact that larger banks tended to acquire other large banks in larger cities that, on average, had more correspondents. In this regard, our findings are consistent with anecdotal evidence from recent crises – large banks become systemically more important, but with our data, we also can show they became systemically riskier.

Table 8: Estimation Results for Size Subsamples

Sample Restriction	# Acquirers	Model 1 Balance Sheet Risk	Model 2 Systemic Risk
Size Quintile 1 – Number Acquired	120	1.379 (0.269)	0.010 (0.003)
Size Quintile 2 – Number Acquired	272	0.503 (0.185)	0.006 (0.002)
Size Quintile 3 – Number Acquired	381	0.642 (0.163)	0.006 (0.002)
Size Quintile 4 – Number Acquired	467	0.631 (0.144)	0.007 (0.002)
Size Quintile 5 – Number Acquired	597	0.169 (0.046)	0.016 (0.003)

This table contains Equation (2) results from two models. Posterior means and standard deviations (in parentheses) are presented. The difference between the two models is the outcome for Equation (2), where we explore the change in balance sheet risk then the change in systemic risk. Each row represents a sample restriction based on bank size quintiles.

4.3.3 Robustness

We explore the robustness of the results shown in Table 6 by omitting banks located in central reserve cities and reserve cities, places where the largest and most-connected banks are located. We perform this sensitivity test to ensure that the relationship between acquisitions and changes in risk changes are not driven by the large banks in these areas, and that the results also hold on the periphery – for county banks located across the United States. Table 9 presents the results for our main covariate of interest, *Number Acquired*. When we remove banks located in reserve and central reserve cities from the sample, the estimate for *Number Acquired* in Equation (2) is 0.491 (0.068) for changes in balance-sheet risk and 0.008 (0.001) for changes in systemic risk. Thus, acquisitions are associated with changes in balance-sheet risk that are nearly twice as large when we remove the largest banks from the system. However, the effect of acquisitions on changes in systemic risk is about 38% smaller in comparison to the effect shown in Table 6, a finding that seems intuitive since the restricted sample omits the central nodes in the correspondent network. Our findings are thus robust to omitting these important regions.

Given that Figure 3 demonstrates slightly different merger behavior in areas where branching is permitted, we examine whether the results shown in Table 6 differ if we restrict the sample to states that allowed some branching versus states that completely prohibited branching. This analysis is displayed in Table 9. In both samples, we find that the number of acquisitions has a positive effect on balance-sheet risk and systemic risk. We find that acquisitions have a much greater influence on changes to systemic risk in areas that allow branching. This result makes sense because branching systems were involved in more M&As. Overall, our main findings are robust to various sample restrictions.

Table 9: Estimation Results for Various Subsamples

Sample Restriction	Model 1 Balance Sheet Risk	Model 2 Systemic Risk
Omitting Reserve Cities – Number Acquired	0.491 (0.068)	0.008 (0.001)
Some Branching Allowed – Number Acquired	0.215 (0.054)	0.212 (0.054)
Branching Prohibited – Number Acquired	0.312 (0.059)	0.012 (0.002)

This table contains Equation (2) results from two models. Posterior means and standard deviations (in parentheses) are presented. The difference between the two models is the outcome for Equation (2), where we explore the change in balance sheet risk then the change in systemic risk. Each row represents a sample restriction.

4.3.4 Alternative Outcomes

Thus far, our results demonstrate that the increase in systemic risk is driven by M&A activity, where balance-sheet risk was transferred from problematic exiting institutions to healthier acquiring institutions that were *a priori* larger and more connected. Another possibility is that acquiring institutions increased their network importance, also influencing systemic risk. To explore how acquisitions change network connectivity, we specify a model where the outcome for Equation (2) is the change in degree for each bank between 1929 and 1934; otherwise, the model is identical to that in Table 6. Table 10 shows that the *Number Acquired* variable in Equation (2) is not statistically different from zero, meaning that acquisitions had no effect on network connectivity. Thus, the positive effect of acquisitions on systemic risk is largely explained by the transfer of risky balance-sheet characteristics onto more centrally-located nodes in the correspondent network.

Our risk measure, R, encapsulates several potential balance-sheet movements, including asset growth, capital shrinkage, and surplus shrinkage. To understand the component(s) driving changes in balance-sheet risk, we consider two models where one outcome for Equation (2) changes to C and the other changes to L, as defined in Equations (11) and (12), respectively. (In order to keep their distributions well-behaved and reduce sensitivity to outliers, these outcome variables remain as defined earlier.) Table 10 shows that acquisitions led to more leveraged banks, at least in the year following a crisis, and consistent with a literature showing similar effects for corporate mergers (Ghosh and Jain, 2000) as well as bank mergers in non-crisis periods (Heggestad and Mingo, 1975). This result suggests that banks may pursue mergers as a way to increase leverage, though it should be noted (as shown in Table 4) that these mergers occurred during a period when, on average, the sample of all banks de-leveraged (perhaps due to the crisis). Referencing Table 4, it appears that, on average, most surviving banks reduced their leverage, except for banks involved in acquisitions.

Finally, because first differences are but one way to assess changes over time, we also consider models where the outcome variable for Equation (2) is growth in R and growth in S. Table 10 shows that the number of acquisitions variable is positively associated with growth in balance sheet risk as well as systemic risk. While our results are robust, we prefer the first difference specifications because those distributions are more well-behaved with fewer outliers.

Table 10: Alternative Outcome Variables for Equation 2

Measures for y_2	Number Acquired
Change in Degree (Degree_{34} - Degree_{29})	-0.031 (0.037)
Change in C (C_{34} - C_{29})	0.013 (0.023)
Change in L (L_{34} - L_{29})	0.048 (0.005)
Growth in R ((R_{34} - R_{29})/R_{29})	0.019 (0.003)
Growth in S ((S_{34} - S_{29})/S_{29})	0.036 (0.015)

This table contains the results for the variable "Number Acquired" in Equation (2) when we consider different outcomes for Equation (2).

5 Concluding Remarks

In the wake of banking crises, failures are sometimes blamed on "overbanking" – that "too many banks" in the system created instability and that banks exits, through mergers and failures, will lead to a less risky financial system by purging the system's excesses – a view that dates back at least to the Great Depression.[11] Our research explores what happens to risk in the financial system as a result of a severe banking crisis and what role both failures and mergers play in altering risk. We examine two types of risk, balance-sheet risk and systemic risk, and construct a new dataset that tracks the exit strategies of every commercial bank in the U.S. between 1929 and 1934 so that we can examine how overall risk to the system changed as well as the factors that drove risk at the micro level. A key contribution of our methodological approach is to highlight the role of M&A activity on risk. To accommodate bank survival selection and nonrandom exit type concerns, we develop a trivariate incidental truncation model.

We find that the largest American financial crisis of the 20$^{\text{th}}$ century did not "purge the rottenness" from the system. Even with thousands of banks failing and exiting the financial system, balance-sheet risk remained elevated and systemic risk increased by 33% more than a year after the crisis ended. We show that mergers acted as an important countervailing force during the crisis. Each acquisition increased the balance-sheet risk of the acquiring bank by 25%. On the eve of the Depression, balance-sheet risk largely resided in small- and medium-sized banks. As these banks exited the system, many were acquired by larger, well-connected banks. Thus, balance-sheet risk made its way onto the portfolios of more central nodes in the financial system, ultimately leading to a substantial rise in systemic risk. Even when mergers involved smaller banks on the periphery, they increased the default risk or balance sheet risk of acquiring banks.

Our findings for both systemic risk and balance-sheet risk suggest that M&A activity during crises is an important channel through which risk is redistributed. In the wake of the global financial crisis of 2007-8, the FDIC and DOJ have stressed the importance of "community needs" and "market competition" in the consideration of purchase and assumption agreements. However,

[11] For example, one conclusion the Federal Reserve drew was, "One of the chief evils of the dual banking system and the accompanying competition for numbers and resources has been manifested in the organization of new hanks. Numerous institutions have been chartered which should never have been allowed to commence business. In their subsequent failure lies a large part of the explanation of the deplorable safety record of our banking structure" (Board of Governors of the Federal Reserve System Committee on Branch, Group, and Chain Banking, 1932, p.48).

in a recent speech by the Vice Chair for Supervision of the Federal Reserve, Michael Barr explicitly expressed concern about the risks that mergers can pose to competition, consumers, and financial stability. In commenting on financial stability, he stated that "these risks may be difficult to assess, but this consideration is critical." We provide a framework to assess these risks and empirically demonstrate the impact on the financial system using the most notorious and widespread American banking crisis of the 20$^{\text{th}}$ century. Our research appears particularly relevant in light of recent policy responses to banking distress that include loss sharing between the acquiring banks and regulators.

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Appendix

Here, we provide the full updating formulas for the Gibbs sampling estimation algorithm. To begin, we define the following vectors and matrices to ease notation.

$$\boldsymbol{\beta} = (\boldsymbol{\beta}_1', \boldsymbol{\beta}_2', \boldsymbol{\beta}_3')' \tag{17}$$

$$\boldsymbol{J}_S = \begin{pmatrix} \boldsymbol{I} & 0 & 0 \\ 0 & \boldsymbol{I} & 0 \end{pmatrix}, \quad \boldsymbol{J}_E = \begin{pmatrix} \boldsymbol{I} & 0 & 0 \\ 0 & 0 & \boldsymbol{I} \end{pmatrix} \tag{18}$$

$$\begin{aligned} \boldsymbol{J}_S\boldsymbol{\beta} &= (\boldsymbol{\beta}_1', \boldsymbol{\beta}_2')'. \\ \boldsymbol{J}_E\boldsymbol{\beta} &= (\boldsymbol{\beta}_1', \boldsymbol{\beta}_3')'. \end{aligned}$$

Gibbs Sampling Algorithm:

Step 1) Update $\boldsymbol{\beta}$ from the distribution: $\boldsymbol{\beta}|\boldsymbol{y}^*, \boldsymbol{\Omega} \sim \mathcal{N}(\boldsymbol{b}, \boldsymbol{B})$, where

$$\boldsymbol{b} = \boldsymbol{B}\left(\boldsymbol{B}_0^{-1}\boldsymbol{b}_0 + \sum_{i\in N_S} \boldsymbol{J}_S\boldsymbol{X}_{iS}'\boldsymbol{\Omega}_S^{-1}\boldsymbol{y}_{iS}^* + \sum_{i\in N_E} \boldsymbol{J}_E\boldsymbol{X}_{iE}'\boldsymbol{\Omega}_E^{-1}\boldsymbol{y}_{iE}^*\right) \tag{19}$$

$$\boldsymbol{B} = \left(\boldsymbol{B}_0^{-1} + \sum_{i\in N_S} \boldsymbol{J}_S\boldsymbol{X}_{iS}'\boldsymbol{\Omega}_S^{-1}\boldsymbol{X}_{iS}\boldsymbol{J}_S' + \sum_{i\in N_E} \boldsymbol{J}_E\boldsymbol{X}_{iE}'\boldsymbol{\Omega}_E^{-1}\boldsymbol{X}_{iE}\boldsymbol{J}_E\right)^{-1}. \tag{20}$$

Step 2) Update $\boldsymbol{\Omega}$ using the conditional distribution $\boldsymbol{\Omega}|\boldsymbol{y}^*, \boldsymbol{\beta}$ in a one-block, four-step procedure. The procedure rests on subsamples for the surviving banks and exiting banks and sampling from inverse-Wishart and normal distributions.

Let $\mathbf{R} = \mathbf{Q} + \sum(\boldsymbol{y}_i^* - \boldsymbol{X_i'}\boldsymbol{\beta}^*)(\boldsymbol{y}_i^* - \boldsymbol{X_i'}\boldsymbol{\beta}^*)'$ which can be represented for each equation system. The following subsections are obtained by partitioning $\mathbf{R}$ to conform to $\mathbf{Q}$, and $\mathbf{R}_{tt\cdot l} = \mathbf{R}_{tt}\mathbf{R}_{tl}\mathbf{R}_{ll}^{-1}\mathbf{R}_{lt}$.

For the surviving banks, sample:

$$\begin{aligned} \omega_{22\cdot 1} &\sim \mathcal{IW}(v + n_1, R_{S,22\cdot 1}) \\ \omega_{21} &\sim \mathcal{N}(R_{S,11}^{-1}R_{S,12}, \omega_{22\cdot 1}R_{S,11}^{-1}). \end{aligned}$$

Defining $\omega_{22\cdot 1} = \omega_{22} - \omega_{12}^2$, we can recover $\boldsymbol{\Omega}_S$.

For the exiting banks, sample:

$$\begin{aligned} \omega_{33\cdot 1} &\sim \mathcal{IW}(v + n_2, R_{E,33\cdot 1}) \\ \omega_{31} &\sim \mathcal{N}(R_{E,11}^{-1}R_{E,13}, \omega_{33\cdot 1}R_{E,11}^{-1}). \end{aligned}$$

Defining $\omega_{33\cdot 1} = \omega_{33} - \omega_{13}^2$, we can recover $\boldsymbol{\Omega}_E$.

Step 3) Update $\boldsymbol{y}^*$ using data augmentation for the binary and ordered outcome variables. We sample from truncated normal distributions with the usual conditional means ($\boldsymbol{\mu}$)and variances ($\boldsymbol{\Omega}$).

For $i : y_{i1} = 0$, sample

$$y^*_{i1}|\boldsymbol{y}, \boldsymbol{y}^*_3, \boldsymbol{\beta}, \boldsymbol{\Omega} \sim \mathcal{TN}_{(-\infty,0)}\left(\mu_{i,E|3}, \Omega_{E|3}\right) \tag{21}$$

For $i : y_{i1} = 1$, sample

$$y^*_{i1}|\boldsymbol{y}, \boldsymbol{y}^*_2, \boldsymbol{\beta}, \boldsymbol{\Omega} \sim \mathcal{TN}_{(0,\infty)}\left(\mu_{i,S|2}, \Omega_{S|2}\right) \tag{22}$$

For $i : y_{i3} = 1$, sample

$$y^*_{i3}|\boldsymbol{y}, \boldsymbol{y}^*_1, \boldsymbol{\beta}, \boldsymbol{\Omega} \sim \mathcal{TN}_{(-\infty,0)}\left(\mu_{i,E|1}, \Omega_{E|1}\right) \tag{23}$$

For $i : y_{i3} = 2$, sample

$$y^*_{i3}|\boldsymbol{y}, \boldsymbol{y}^*_1, \boldsymbol{\beta}, \boldsymbol{\Omega} \sim \mathcal{TN}_{(0,1)}(\left(\mu_{i,E|1}, \Omega_{E|1}\right) \tag{24}$$

For $i : y_{i3} = 3$, sample

$$y^*_{i3}|\boldsymbol{y}, \boldsymbol{y}^*_1, \boldsymbol{\beta}, \boldsymbol{\Omega} \sim \mathcal{TN}_{(1,\infty)}\left(\mu_{i,E|1}, \Omega_{E|1}\right) \tag{25}$$

In a simulation study, the algorithm performs well. It is fast and efficient while maintaining the tractability of the sampling densities. Further, inefficiency factors were low, getting a near *iid* posterior sample.