NBER WORKING PAPER SERIES

FAILING BANKS

Sergio A. Correia
Stephan Luck
Emil Verner

Working Paper 32907
http://www.nber.org/papers/w32907

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02139
September 2024

We would like to thank our discussants Jorge Abad, Matt Baron, Asaf Bernstein, Mark Carlson, Tim Eisert, Daniel Ferreira, Matt Jaremski, Joseph Mason, Andrew Metrick, Manju Puri, Eva Schliephake, Skander van den Heuvel, and Kaspar Zimmermann for their invaluable comments. We would also like to thank Viral Acharya, Rosalind Bennett, Michael Bordo, Harry Cooperman, Natalie Cox, Darrell Duffie, Robin Greenwood, Kinda Hachem, Ing-Haw Cheng, Sam Hanson, Barney Hartman-Glaser, Ben Hebert, Bev Hirtle, Òscar Jordà, Nobu Kiyotaki, James McAndrews, Thomas Philippon, Matt Plosser, Andrei Shleifer, Hyun Shin, Jon Steinsson, Adi Sunderam, Eugene White, and seminar participants at Auburn University, Bank for International Settlements (BIS), Banco de Portugal and CEPR Conference on Financial Intermediation, 2024 WFA Hawaii, 2024 Barcelona Summer Forum, Cowles Foundation Conference on Rethinking Optimal Deposit Insurance, Federal Reserve Board, Federal Reserve Monetary and Financial History Workshop, George Washington University, Harvard-MIT Financial Economics Workshop, MIT Sloan, 2024 MoFiR Workshop on Banking, 2024 NBER Financial Market Frictions and Systemic Risks, 2024 NBER Summer Institute Corporate Finance, Northwestern Conference on Historical Lessons for Monetary and Fiscal Policy, NYU Stern, Rutgers University, Office of the Comptroller of the Currency (OCC), Fed-Maryland Short-Term Funding Markets Conference, UC Berkeley Econ, UC Berkeley Finance, USC Macro-Finance Conference, University of Toronto Conference on Banks, States and the People: Origins and Impact of Banking Crises, University of Zurich, University of Tilburg, the University of Maastricht, and the Yale Program on Financial Stability for useful comments. We also would like to especially thank Natalie Girshman and Francis Mahoney for help with archival work and Rosalind Bennett for sharing the FDIC's Failure Transaction Database. We thank Gabriel Leonard and Tiffany Fermin for excellent research assistance. The project has received support from the MIT Research Support Committee's Ferry Fund. The opinions expressed in this paper do not necessarily reflect those of the Federal Reserve Bank of New York, the Board of Governors of the Federal Reserve System, or the National Bureau of Economic Research.

Failing Banks
Sergio A. Correia, Stephan Luck, and Emil Verner
NBER Working Paper No. 32907
September 2024
JEL No. G01, G21, N20, N21, N22

ABSTRACT

Why do banks fail? We create a panel covering most commercial banks from 1865 through 2023 to study the history of failing banks in the United States. Failing banks are characterized by rising asset losses, deteriorating solvency, and an increasing reliance on expensive non-core funding. Commonalities across failing banks imply that failures are highly predictable using simple accounting metrics from publicly available financial statements. Predictability is high even in the absence of deposit insurance, when depositor runs were common. Bank-level fundamentals also forecast aggregate waves of bank failures during systemic banking crises. Altogether, our evidence suggests that the ultimate cause of bank failures and banking crises is almost always and everywhere a deterioration of bank fundamentals. Bank runs can be rejected as a plausible cause of failure for most failures in the history of the U.S. and are most commonly a consequence of imminent failure. Depositors tend to be slow to react to an increased risk of bank failure, even in the absence of deposit insurance.

Sergio A. Correia
Board of Governors of the
Federal Reserve System
sergio.correia@gmail.com

Stephan Luck
Federal Reserve Bank of New York
33 Liberty St
New York, NY 10045
stephan.luck@ny.frb.org

Emil Verner
MIT Sloan School of Management
100 Main Street, E62-635
Cambridge, MA 02142-1347
and NBER
everner@mit.edu

A data appendix is available at http://www.nber.org/data-appendix/w32907

1 Introduction

Bank failures are an inherent feature of banking. In the United States, 20.4% of all national banks in existence from 1863 to 1934 and around 13% of all commercial banks in existence from 1935 to 2023 failed at some point during these periods. Bank failures often lead to real economic disruptions (Bernanke, 1983), and systemic banking crises featuring widespread bank failures are associated with severe macroeconomic downturns (Reinhart and Rogoff, 2009).

What causes bank failures? Theory offers two main explanations for why banks fail. Bank failures can be the consequence of *bank runs* in which depositors collectively withdraw from otherwise solvent (Diamond and Dybvig, 1983) or troubled but solvent banks (Goldstein and Pauzner, 2005). Bank runs are cited as an important cause of bank failures and amplification in prominent accounts of the Great Depression (Friedman and Schwartz, 1963), the 2008 Global Financial Crisis (Bernanke, 2018), and the bank failures in spring 2023. An alternative view is that bank failures are caused by poor *fundamentals* such as realized credit risk, interest rate risk, or fraud, which trigger insolvency irrespective of whether a bank run takes place or not (e.g., Temin, 1976; Wicker, 1996; Calomiris and Mason, 1997; Admati and Hellwig, 2014; Gennaioli and Shleifer, 2018).

This longstanding debate raises several important questions. Which type of failures are empirically most relevant? Are bank failures primarily a result of bank runs or are they more commonly caused by a deterioration of fundamentals? When runs do occur, are they merely a symptom of weak fundamentals or a primary cause of failure?

Understanding the potential determinants of bank failures empirically, however, is challenging. Government interventions such as deposit insurance and lending of last resort reduce the scope for bank runs to cause bank failures in modern times (Metrick and Schmelzing, 2021). A common argument for these interventions is precisely to prevent failures caused by runs, especially on otherwise solvent banks. Thus, observed bank failures in modern times may be biased towards failures involving poor fundamentals.

To overcome this challenge, we study the history of failing banks in the United States from 1865 to 2023. We construct a new database with balance sheet information for most banks in the U.S. since the Civil War. Our data consist of a historical sample that covers all national banks from 1865 to 1941 and a modern sample that covers all commercial banks from 1959 to 2023. Altogether, our data contain balance sheets for around 37,000 distinct banks, of which more than 5,000 fail. This rich sample thus covers failures both before and after the founding of the Federal Reserve System and the introduction of deposit insurance from the Federal Deposit Insurance Corporation (FDIC). Hence, this sample allows us to study bank failures during historical episodes in which bank runs could plausibly have been a common cause of bank failures.

We begin by documenting three facts about commonalities in failing banks which are robust across different institutional settings. First, failing banks see a rise in non-performing loans and deteriorating solvency several years before failure. In failure, banks commonly have large unrealized losses on assets. For example, losses on assets held at failure average 49% in the historical sample, resulting in substantial losses to depositors before deposit insurance. Second, failing banks increasingly rely on expensive and risk-sensitive non-core funding in the run-up to failure. Third, failing banks undergo a boom-and-bust in assets during the decade before failure. Asset losses thus often follow a period of rapid loan growth.

Next, we show that bank failures are remarkably predictable using accounting metrics from publicly available financial statements that indicate deteriorating fundamentals. We first illustrate this by showing that the probability of failure increases in both observable measures of insolvency risk (proxying the distance to default using either bank capitalization, income, or non-performing loans) and funding vulnerabilities (proxying the reliance on expensive and risk-sensitive types of funding such as wholesale deposits or non-deposit wholesale funding). For example, a bank in the top 5$^{\text{th}}$ percentile of both insolvency risk and funding vulnerability has a probability of failure over the next three years of at least 13% and up to 42%, depending on the sample period. This amounts to a 10- to 40-fold increase in the probability of failure relative to the average bank, a large differential.

We quantify the extent of predictability by estimating simple regression models in which we predict whether a bank will fail based on simple measures of a bank's insolvency and funding vulnerability constructed from publicly available financial statements. We assess predictability based on the area under the receiver operating characteristic curve (AUC), a common measure of performance for binary classifiers. In the historical, pre-FDIC sample, the AUC for predicting failure next year is between 83-90%, indicating a high degree of predictability. In the modern sample, after the introduction of deposit insurance, the predictability of bank failures is even higher, with an AUC between 90-95%. In both the historical and modern samples, the predictability of failures is typically nearly as high in pseudo-out-of-sample as in in-sample forecasting exercises.

The high predictability of bank failures extends to failures involving bank runs. We specifically study failures with large deposit outflows, which are indicative of bank runs, and contrast these to failures without large deposit outflows. We first establish that deposit outflows immediately before failure were much larger in the pre-FDIC era. While deposits in failing banks decline on average by around 2% between 1959 and 2023, they fall on average by 12% in the pre-1934 sample. Nonetheless, perhaps surprisingly, we find that even for the pre-FDIC sample period, when depositors typically realized large losses when banks failed, not all failures were preceded by bank runs. In around 25% of failures before 1934, deposits did not decline at all or only minimally. Further, we find that failures with large deposit outflows are at least as easy to predict as failures without large deposit outflows. Hence, banks that exit with a run can be identified as weak banks based on their financial fundamentals before the run happens.

We also study classifications of causes of bank failures provided by contemporary bank examiners from the Office of the Comptroller of the Currency (OCC). Notwithstanding the common occurrence of large deposit outflows in the run-up to failure, from 1865 through 1937, most bank failures were classified by the OCC as being caused by losses, fraud, or external economic shocks. Despite popular narratives about banking panics playing a key role in the historical U.S. banking system, runs and liquidity issues account for less than 2% of failures classified by the OCC.

Weak bank fundamentals not only predict individual bank failures. They also forecast waves of banking failures during systemic banking crises. We aggregate the out-of-sample forecasts of individual bank failure risk to predict the aggregate bank failure rate. The R^2 of a regression of the actual bank failure rate on the predicted aggregate failure rate is 71%. Thus, spikes in bank failures during systemic banking crises cannot merely be explained by panics. Instead, waves of failures are strongly accounted for by deteriorating fundamentals.

In the final part of the paper, we ask: What do the facts we bring forward imply about the causes of bank failures and the nature of banking crises? Are observed bank failures more commonly caused by bank runs or insolvency? It is important to emphasize that our empirical approach does not allow us to identify the causes of individual bank failures definitively. Nonetheless, we can make inferences about the relative importance of runs versus insolvency by contrasting our findings with simple predictions of bank run models.

We make use of the following three predictions of theories of bank runs. First, failures due to bank runs on otherwise solvent banks should at best exhibit a modest degree of predictability (Gorton, 2012; Greenwood et al., 2022). In models of panic runs, bank failures cannot be substantially predictable, as attentive depositors would act on this information and withdraw their funds, reducing the predictability in the first place. Second, for bank runs to represent the cause of bank failure, failing banks should experience large deposit outflows that force them to liquidate their otherwise valuable assets or engage in other activities that erode solvency. Third, recovery rates on assets in failures should be relatively high in failures caused by a run, as banks mostly hold securities and loans that can be separated and repossessed.[1] On the other hand, recovery rates should be low if deteriorating asset quality drives a bank to insolvency irrespective of a run.

Altogether, our findings suggest that the scope for bank runs to represent a common cause of bank failures is limited, even in the absence of deposit insurance. Consider for instance purely self-fulfilling panics as in Diamond and Dybvig (1983). These runs should not be related to fundamentals but strike randomly (see, e.g., Greenwood et al., 2022), feature large deposit outflows before failure, and exhibit relatively low losses in failure. We find that bank failures that were not predicted by bank fundamentals (defined as an out-of-sample predicted probability to fail over a three-year horizon of less than 2.5%), featured large deposit outflows (a decline in deposits of 7.5% before failure), and exhibited relatively modest losses in default (recovery rates in default of above 75%) are extremely rare and make up less than 0.5% of pre-FDIC failures. This fact suggests that Diamond-Dybvig-style bank runs that cause the failure of otherwise healthy banks are unlikely to have been driven into extinction by deposit insurance. Rather, they have never been an empirically relevant cause of bank failures to begin with.

Further, our findings also have implications for the empirical relevance of theories of runs on troubled but solvent banks (Goldstein and Pauzner, 2005; Rochet and Vives, 2004; He and Xiong, 2012). We document that when runs on failing banks do occur, they tend to happen in banks with weak observable fundamentals. Our paper thus generalizes insights from existing empirical studies that have focused on studying specific episodes (see, e.g., Calomiris and Mason, 1997, 2003; Iyer and Puri, 2012) and establishes that weak fundamentals are a necessary condition for a bank run to happen both outside and during financial crises, and both with and without deposit insurance.

[1] The scope of a bank run to destroy value stems mainly from destroying a bank's franchise value rather than reducing the value of assets still held after bank closure. Recent estimates suggest that a bank franchise value is on the order of 20% (Ma and Scheinkman, 2020; Hirtle and Plosser, 2024). Hence, for a bank run to have plausibly been the cause of failure, the recovery rate on assets in failure should not be lower than 80%.

However, we also find that the scope for bank runs to cause the failure of weak but solvent banks is surprisingly limited. Runs on solvent but troubled banks should exhibit low to moderate predictability, large deposit outflows, and moderate losses. However, we find that less than 15% of all pre-FDIC failures fulfill these criteria. In contrast, we find that more than 80% of pre-FDIC failures were characterized by either a high predicted probability of failure (above 7.5%), no deposit outflows, or large asset losses (recovery rates in receivership of less than 50%). Hence, in most bank failures, depositors either did not run, or they withdrew their funds from banks that were most likely already insolvent.

Further, we find that 23% of failures exhibit a very high degree of out-of-sample predicted probability failure over three years of more than 20% in the year before failure. Arguably, any bank with such a high predicted probability of failure cannot be viable if depositors would require compensation for being exposed to such a high risk of bank failure. Thus, the fact that these banks have not failed yet and we as econometricians can observe high predicted failure probabilities suggests that depositors are often slow to react to an increased risk of bank failure. Bank runs, to the extent they happen, seem to happen later than theoretical benchmarks would suggest. This fact, in turn, points to a role for behavioral frictions such as inattentive depositors or neglect of downside risk (e.g., Gennaioli et al., 2012; Jiang et al., 2023).

Taken together, our findings suggest that most bank failures are the result of a deterioration in bank solvency. The erosion of a bank's capitalization ultimately results in either a run or a supervisory decision to close a bank, with the former being more common in the historical data. Importantly, both depositors and supervisors seem to be slow to react to information about bank fundamentals, thus making bank failures highly predictable. Our findings suggest that we can reject bank runs as a plausible cause of failures for a robust majority of banks that failed in the history of the United States.

Related literature. Our paper relates to two strands of literature on bank failures and financial crises.

First, we relate to micro-level studies of bank failures and banking crises, such as empirical studies of the Great Depression (e.g., Calomiris and Mason, 1997, 2003; Mitchener and Richardson, 2019), the 2008 Global Financial Crisis (e.g., Gorton and Metrick, 2012; Krishnamurthy et al., 2014; Schmidt et al., 2016), the recent banking stress in March 2023 (e.g., Jiang et al., 2023), and other episodes featuring bank runs (Iyer and Puri, 2012; Frydman et al., 2015; Iyer et al., 2016; Artavanis et al., 2022).[2] The novelty of our approach is to bring together evidence from roughly 160 years of micro-level data that spans a range of institutional and regulatory regimes. Studying the close-to-complete history of the banking system in the United States allows us to generalize the insight that weak fundamentals are a necessary condition for bank failures across various institutional settings, both during financial crises but also quiet periods. While existing micro-level studies usually condition on a crisis, our long sample demonstrates that failures and banking crises are predictable out-of-sample. Moreover, the richness of the data allows us to provide robust facts about the predictability of bank failures, deposit outflows before failure, and losses realized in failure. Contrasting these facts with testable predictions of bank run models, in turn, establishes that bank runs do not qualify as a plausible cause of failure in the majority of pre-FDIC failures.

Second, our paper is related to studies of financial crises using aggregate data. Within this literature, our paper relates most closely to studies on the nature of banking crises and the sources of bank failures and panics. Gorton (1988) and Calomiris and Gorton (1991) study banking panics in the National Banking Era and find that panics generally

[2] Several of these studies focus on explaining banking failures during specific episodes in the U.S. Calomiris and Mason (2003) find that fundamentals explain bank failures in the Great Depression, rather than panic-driven depositor flight. Using state-level data Alston et al. (1994) find that failures in the 1920s were highest in states that saw the largest growth in agricultural acreage during WWI, and most failing banks were small and rural. Studies using recent Call Report data find that highly levered banks, banks with low earnings, low liquidity, and risky asset portfolios are more likely to fail (Wheelock and Wilson, 2000; Berger and Bouwman, 2013).

followed bad macroeconomic news but were not important for bank failures. Baron et al. (2021) argue that panic runs are not necessary for banking crises, and panics are preceded by bank equity declines, reflecting the realization of bank losses. Our paper provides complementary evidence by using granular bank-level data.[3] This allows us to show that deteriorating fundamentals are necessary for both individual and widespread bank failures, including failures with runs. Moreover, it allows us to provide micro-data evidence that the underlying cause of individual bank failures during systemic banking crises is deteriorating solvency.

The cross-country literature on banking crises finds that rapid credit growth is a robust predictor of systemic banking crises (Borio and Lowe, 2002; Schularick and Taylor, 2012; Baron and Xiong, 2017; Greenwood et al., 2022; Müller and Verner, 2023). We find that rapid asset growth often precedes bank losses and bank failures. Thus, the boom-bust notion documented in earlier studies carries through to the individual bank level (see also Fahlenbrach et al., 2018; Meiselman et al., 2023). Jordà et al. (2020) find that higher banking system capitalization is not associated with a lower chance of banking crises but does predict stronger recovery from crises. Our bank-level findings indicate that higher bank capitalization predicts a lower probability of failure. Moreover, we show that a banking crisis is imminent when a sufficiently large set of banks is subject to deteriorating fundamentals at the same time. Importantly, this implies that micro-data contain information not available in aggregated country-level statistics that allow for the prediction of banking crises.

Roadmap. The paper proceeds as follows. Section 2 describes the data. Section 3 provides new facts about failing banks. Section 4 presents evidence on the predictability of bank failures. Section 5 studies bank failures with and without runs. Section 6 shows that bank-level fundamentals predict the major waves of bank failures in the U.S. Section 7

[3] See Baron et al. (2023) for another recent paper using granular bank-level data to study many banking crises.

discusses how our findings relate to theories of bank failures and banking crises, and Section 8 concludes. Appendix A provides an overview of the evolution of bank failures and the regulatory framework for banks in the U.S. since 1863.

2 Data

Data for historical sample (1865-1941). We use two main data sources on bank balance sheets. Data on national bank balance sheets from 1865 through 1941 are from the Office of the Comptroller of the Currency's (OCC) Annual Report to Congress. For most of the sample, the balance sheets were reported as of September or October of each year, but from 1928 onward the reporting date shifted to the end of each year. The data are quite granular. In addition to broad line items such as total assets, loans, deposits, and equity, for most years banks also report more detailed items that allow us to measure non-performing loans and wholesale funding. However, the OCC did not require banks to report income statements. Figure C.1 and Figure C.2 in Appendix C.1 provide examples of the original source.

Data on all national banks in existence from 1865 until 1904 are digitized and provided by Carlson et al. (2022). For this project, we further digitize bank balance sheets from 1905 through 1941. In both cases, balance sheets are digitized using optical character recognition (OCR), applying the methods discussed in Correia and Luck (2023). We hand-check the OCR output, with particular attention to cases where accounting identities fail to hold and drop observations that violate accounting identities otherwise. Moreover, we compile a list of all significant bank events and their dates—chartering, liquidations, receiverships, etc.—from 1863 to 1935 using data manually collected by van Belkum (1968), augmented by Huntoon (2023), and further validated by the authors using information from the 1941 "Alphabetical List of Banks" (Office of the Comptroller of the Currency, 1941), as well as the corresponding OCC Annual Reports.

We define a national bank as a failed bank whenever a receiver is appointed by the OCC. Note that our definition of failure includes banks that eventually exit receivership and continue operating, and banks that exit receivership and wind down their operations in an orderly voluntary liquidation that imposes no losses to creditors. However, our definition of bank failure excludes bank closures that did not involve a receiver at some point. Moreover, we exclude temporary suspensions in which banks briefly suspend convertibility of their debt into cash and then reopen, as was common during banking panics of the National Banking Era. This implies that we also exclude banks that averted receivership due to cooperation through, for example, bank clearinghouses. We emphasize this distinction, since the factors that lead to bank runs that are resolved by temporary suspension of convertibility may differ from those that lead to bank failures.

The OCC collected detailed information on the post-mortem developments of failing banks. This information is also recorded in the OCC's annual report.[4] These data provide information on the nominal amount of assets and deposits at the moment a bank's business was suspended and a receiver was appointed. Thus, they allow us to calculate the outflow of resources and deposits between the last call report and the failure date. There is also information on asset quality, as the OCC provides estimates of the breakdown of "good," "doubtful," and "worthless" assets at suspension. Furthermore, the data report the funds ultimately collected by the receiver throughout the receivership proceedings. It thus allows us to estimate the recovery rates on assets in failure. The data also contain the recovery rate for depositors. Finally, the OCC classified bank failures by the cause of failure for most failures between 1865 and 1937, with the exception of failures that occurred in 1932 and 1933. Further details on these data are provided in Appendix C.2.

For the period before the founding of the FDIC, we rely entirely on data on national

[4]The OCC annual report from 1920 reports data for all failed national banks from 1863 through 1920 comprehensively. Thereafter, we digitize each OCC's annual report table on national banks in charge of receivers from 1921 through 1939.

banks. The main reason for focusing on national banks is the availability of consistent records provided by the OCC on both balance sheets and bank failures. However, it is important to highlight that the US banking system featured several types of financial institutions that were not chartered under federal law but state law. National banks always coexisted alongside state banks, trusts, and private banks, with the relative importance of each type of institution varying over time. For example, national banks had a market share of the entire banking market ranging from around 80% in the 1870s to around 45% in the 1930s. See Figure A.2 in the Appendix for details on the number and market share of national banks, as well as White (1983).

Data for modern sample (1959-2023). For the modern, contemporary banking system we use the Federal Financial Institutions Examination Council (FFIEC) Consolidated Reports of Condition and Income ("Call Report"). These data provide quarterly information on balance sheets (FFIEC010) and income statements (FFFIEC013) on a consolidated basis for all commercial banks operating in the United States and regulated by the Federal Reserve System (FRS), the FDIC, and the OCC. Note that most existing research based on the Call Report uses the data starting from 1976 onwards. We extend our sample further back to 1959. These data are digitally available at the Federal Reserve from 1959 through 2023. We also merge additional information on bank charters, such as bank founding dates and the primary regulator using the National Information Center (NIC) tables.

We complement the call report data with the FDIC's list of failing banks. This list documents all failures of FDIC member banks from 1934 through 2023 and is available on the FDIC homepage. We define a bank failure as a bank closure.[5] We obtain the failure dates from the list of failing banks. Further, we obtain deposits and total assets at the

[5]Bank closures involve either a purchase of the failing bank with an assumption of some or all of its deposits or a liquidating receivership. Note that the FDICs failure definition is broader. The FDIC defines a bank failure as the closing of a bank by regulators or an instance of open bank assistance. In the former case, the FDIC acts as receiver of the failed bank. In the latter, the FDIC provides financial assistance to prevent failure under a systemic risk exception; the bank would likely have failed without assistance. While we drop the latter, we note that all findings are robust to broadening the failure definition to include open bank assistance.

time of resolution for failures since 1992 from the FDIC's Failure Transaction Database, which we use to calculate deposit and asset growth immediately before failure.

The financial statements we use are at an annual frequency until 1941. After 1959, balance sheets are reported at a biannual frequency before becoming quarterly in 1976. Unless otherwise stated, we use annual data for our analysis to ensure comparability across different eras. We also drop *de novo* banks from the analysis, which we define as banks younger than four years, since the determinants of failure for these banks can be different.[6]

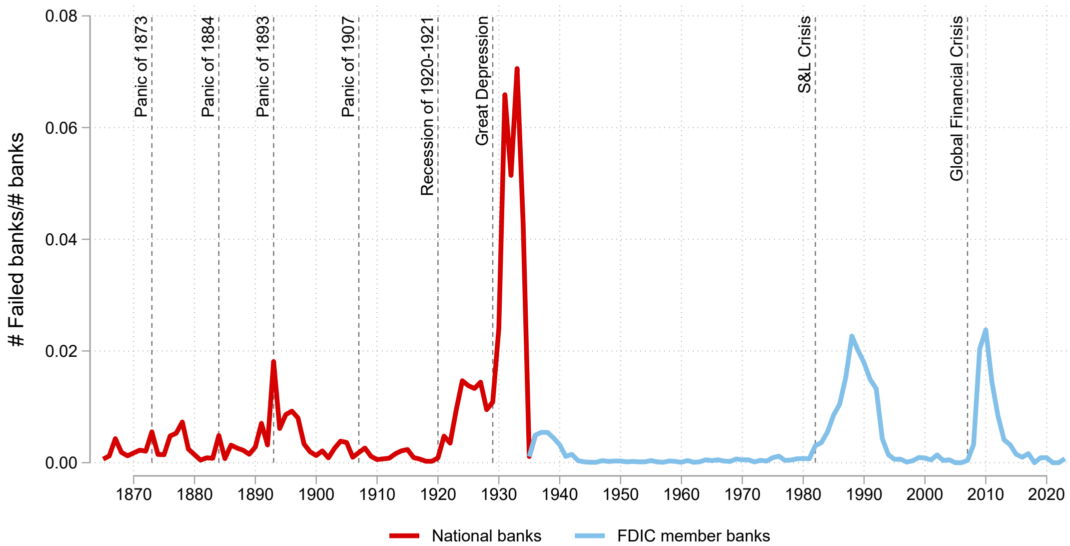
Altogether, our sample consists of 37,498 unique banks.[7] Of these banks, 5,111 banks fail at some point throughout the sample period. Of these failing banks, 2,904 fail before 1935 and 2,207 fail after 1959. Figure 1 plots the rate of bank failures over time. The figure highlights that our sample includes the major financial crises in the history of the U.S., including the Great Depression and the 2008 Global Financial Crisis, as well as many quiet periods when bank failure rates were low. Moreover, our sample covers the period after the founding of the Federal Reserve in 1913 and the founding of the FDIC in 1933, as well as the period before both institutions were operative. Hence, our sample covers an extensive period before the advent of a lender of last resort, deposit insurance, or other forms of government intervention.

Other data. Finally, we use the consumer price index from Global Financial Data to deflate variables that we compare across time. Further, we use aggregate outcomes such as GDP and aggregate credit growth from Jordà et al. (2017) and banking crisis dates from Baron et al. (2021).

[6] The results are very similar when including these banks.

[7] Note that we assign different bank identifies in the OCC data and the Call Report data, thus treating potentially the same bank as different entities before and after Great Depression and the founding of the FDIC. Mechanically, this increases the total number of unique entities.

Figure 1: ***Failing Banks, 1865-2023***



Notes: This figure plots the ratio of bank failures to the total number of banks. Vertical lines indicate selected major banking crises and economic downturns. The red line plots the rate of failing national banks, defined as national banks placed into receivership. Figure A.3 in the Appendix shows suspension rates for both national banks and state-chartered institutions. The blue line plots the rate of banks classified as failed by the FDIC. We restrict our sample of FDIC member banks to National Member Banks, State Member Banks, and State Nonmember Banks and exclude Savings Associations, Savings Banks, and Savings and Loans.

3 Three Facts About Failing Banks

This section documents three facts about failing banks over the past 160 years. First, we show that failing banks see gradually deteriorating solvency before failure and large asset losses in failure. Second, failing banks increasingly rely on non-core funding. Third, failing banks follow a boom-bust pattern. Altogether, these facts point to the central role of deteriorating bank fundamentals in bank failures over the past 160 years.

3.1 Losses and solvency dynamics

Fact 1. Failing banks see rising losses and deteriorating solvency before failure.

To study the dynamics in failing banks before their failure, we estimate variants of the following specification:

$$y_{b,t} = \alpha_b + \sum_{j=-10}^{0} \beta_j \times \mathbf{1}_{j=t} + \epsilon_{b,t}, \tag{1}$$

where $y_{b,t}$ is a bank-level outcome, j measures the number of years to failure, and α_b is a bank fixed effect. All variables in levels are deflated by the CPI. Here, we restrict the sample to failing banks that are within 10 years of failure; we compare the dynamics of failing banks to other banks in the next section. We set the benchmark period to be $j = -10$, so all estimates are relative to ten years before failure. The sequence of coefficients $\{\beta_j\}$ captures the dynamics of variable $y_{b,t}$ in the ten years before failure.

We begin by studying the dynamics in indicators of loan losses and solvency in Figure 2. Panel (a) presents evidence for the post-1959 sample. In the five years before failure, there is a 10-percentage point rise in non-performing loans (NPLs). This rise in NPLs translates into rising loan loss provisions, which results in a decline in realized net income. The fall in net income depresses the return on assets by 5 percentage points in the year before failure. As a result, the equity-to-assets ratio declines considerably in the run-up to failure, falling by 10 percentage points.

The patterns in Figure 2a suggest that failures are mainly associated with realized credit risk, rather than a deterioration in the net interest margin (NIM). The NIM is stable in the run-up to failure. In Appendix Figure B.2 we show that failing banks see both rising interest income (indicating higher risk taking) *and* rising interest expenses (in line with higher reliance on expensive forms of funding, as discussed below). Abstracting from valuation effects of holding long-dated fixed-rate securities, the resulting stable NIM suggests that the realization of interest rate risk is not a first-order source of failure for most failing banks. This is consistent with banks engaging in maturity transformation without taking on substantial interest rate risk due to the predominance of interestinsensitive deposit finance (Drechsler et al., 2021).[8]

Panel (b) in Figure 2 illustrates the evolution of proxies for losses in the 1865-1934 sample. In historical accounting data, banks do not provision for losses, so their equity was not immediately impacted when loans became non-performing. However, reported line items in national bank balance sheets allow us to construct several proxies for deteriorating solvency and rising losses. First, we use the ratio of surplus profit to equity to proxy a bank's capitalization.[9] Second, under capital regulation in the National Bank Act, banks would likely face restrictions on dividend payouts when undivided profits fell close to zero (White, 1983).[10] We therefore proxy for low capitalization with an indicator for whether undivided profits fall short of 1% of total bank equity. This measure is available for 1865-1904 and 1929-1934. Third, we proxy for non-performing loans with the balance sheet item "Other Real Estate Owned" (OREO). This item reflects collateral seized and held on a bank's balance sheet, usually following foreclosure, and it is available for 1889-1904.[11]

Figure 2b shows that failing banks see a deterioration in surplus profits relative to equity, indicating declining profitability and capitalization. As a result, there is a 20 percentage point rise in the likelihood that dividend payouts are restricted due to low capitalization. Moreover, non-performing loans as a share of total loans rises gradually by 15 percentage points in the decade before failure, a pattern similar to the finding for the modern sample.

[8] Even restricting to the 1970s and 1980s, we do not find evidence that failing banks experienced deteriorating net interest margins. This is consistent with Wright and Houpt (1996), who find that *thrifts* saw falling NIM in early 1980s, while commercial banks had much more stable NIM. (We thank Sam Hanson for pointing us to this reference.)

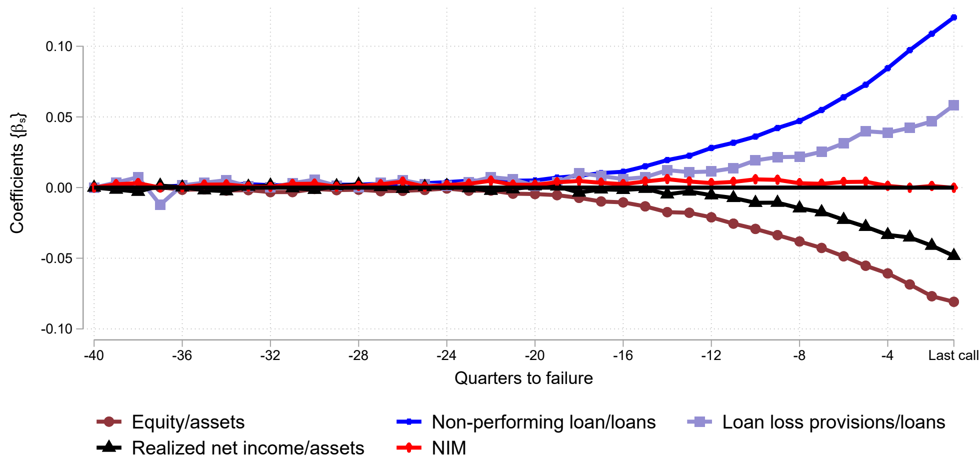
[9] The surplus profit is the sum of the surplus fund and the undivided profits. Capital paid-in was fixed after the founding of a bank and the surplus profit is the portion of equity that was allowed to vary with retained earnings and realized losses.

[10] Fluctuations in bank profitability are reflected in the line item "undivided profits." This item represents funds that could be paid out as dividends to bank shareholders.

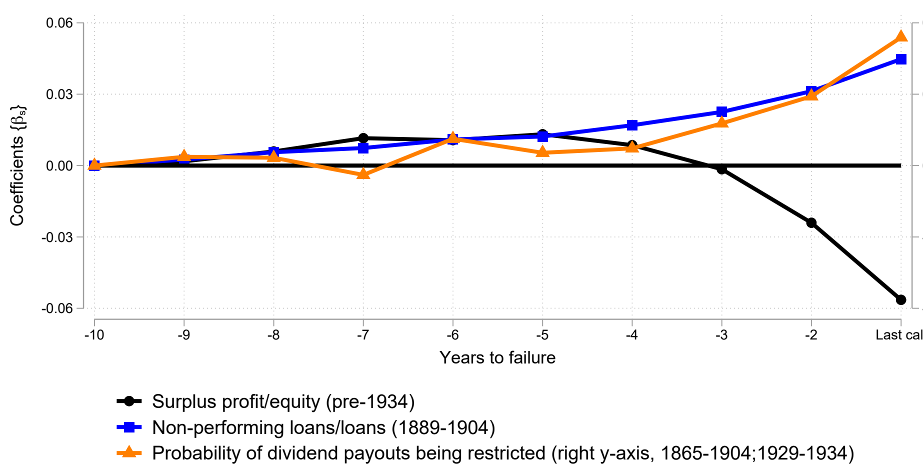
[11] OREO typically refers to real estate property assets that a bank holds but that are not part of its business. Often, these assets are acquired due to foreclosure proceedings and are comparable to seized collateral. In Appendix Figure B.1, we document that OREO as share of loans for failing banks immediately before failure is strongly correlated with the share of assets classified as doubtful or worthless by the OCC in failure.

Figure 2: ***Losses and Solvency of Failing Banks: 1865-2023***

(a) *1959-2023*



(b) *1865-1934*



Notes: The figure presents the sequence of coefficients from estimating Equation (1), where the dependent variable is the ratio indicated in the figure legend. The specification includes a set of bank fixed effects. The sample in both panels is restricted to failing banks and the ten years before they fail. In panel (a), the sample is restricted to banks that failed from 1959 through 2023. In panel (b), the sample is restricted to banks that failed from 1865 through 1934. In panel (a), the net interest margin (NIM) is defined as the difference of total interest income net of interest expenses normalized by total assets. In panel (b), surplus profit to equity is the sum of the surplus fund and undivided profits relative to total equity capital (paid-in capital, undivided profits, and surplus fund). Non-performing loans is proxied by the line item "Other real estate owned (OREO)" and is available for the 1889-1904 subsample. Figure B.1 in the Appendix shows that OREO listed in the last call report before failure is strongly correlated with assets classified as doubtful or worthless in failure by the OCC. The probability of dividend payouts being restricted is based on the share of banks with undivided profits of total equity falling short of 1%. This measure captures restrictions on dividend payouts due to low capitalization and is available for 1865-1904 and again after 1929.

Table 1: *Asset Quality and Recovery Rates in Failure, 1865-1939*

Era	(1) No. of failures	(2) Assets at suspension: Good	(3) Doubtful	(4) Worthless	(5) Received after suspension	(6) Ultimate recovery from assets
1865-1913 (NB Era)	531	0.36	0.40	0.26	0.11	0.45
1914-1928 (Early Fed)	652	0.35	0.40	0.26	0.11	0.48
1929-1934 (Great Depression)	1710	0.36	0.52	0.13	0.08	0.53
All	2893	0.36	0.47	0.18	0.09	0.51

Notes: This table reports estimates of the share of good, doubtful, and worthless assets at the time of suspension, as well as asset recovery rates for failed banks. The sample covers failed national banks from 1865 to 1934. Data are collected from the OCC's annual report to Congress; tables on "National banks in charge of receivers," (various years). Good, doubtful, and worthless assets at suspension are normalized by total assets at suspension. Assets received after suspension (5) and the ultimate recovery from assets (6) are reported as a share of total assets at suspension plus assets received after suspension. The "ultimate recovery from assets" is the total collected funds in receivership relative to total assets. This represents the share of assets that the receiver was ultimately able to recover to compensate debt holders. Note that the receiver also collected funds from shareholders due to double-liability, which increased the overall amount of available funds to distribute to debt holders.

Failing banks in the pre-FDIC period had highly troubled assets and large unrealized asset losses in failure, in line with losses on past investments playing a key role in failures. Table 1 provides statistics on the assets of failing banks at the time of suspension and the ultimate recovery from assets for the 1865-1934 sample. The ultimate recovery from assets represents the value that the receiver was able to obtain from both assets available at suspension and received after suspension. Recovery rates from assets were low in the pre-FDIC sample, averaging 45% to 53%, indicating that many banks were deeply insolvent once they entered receivership.

Further, bank examiners usually judged the assets of failing banks to be highly troubled. The columns "Assets at suspension" in Table 1 indicate estimates of the share of "good," "doubtful," and "worthless" assets provided by the OCC bank examiner at the time of failure. Worthless assets range from 13% to 26% of total assets, depending on the era considered. Doubtful assets represent another 40% to 52%. Table B.3 in the

Appendix shows that asset recovery is well predicted by the bank examiner's assessment of asset quality around the time of failure. On average, one additional dollar of "Good," "Doubtful, and "Worthless" assets resulted in a recovery 78 cents, 45 cents, and 10 cents, respectively. The fact that examiners predicted a low recovery rate for a large part of a failed banks' asset holdings suggests that unrealized losses relative to the book value of assets were potentially a key trigger of failure.[12] That is, while it is in principle possible that values and recovery rates may drop *because* the bank closed, the extent of losses and the fact that examiners identified 64% of assets as having doubtful or worthless value right at the time of suspension suggest that most losses stemmed from past investments going bad.

The low recovery rate on assets in the pre-FDIC sample implies that loss rates for depositors were substantial. Table B.4 in the Appendix presents estimates on the loss rates for uninsured depositors for bank failures in the pre- and post-FDIC samples. Loss rates for uninsured depositors were significantly higher before the founding of the FDIC. In the pre-FDIC sample, 81% of failures involved losses for depositors, and the average unconditional depositor recovery rate (loss rate) is 65% (35%). Moreover, depositors often experienced a substantial delay before receiving their funds. On average, the depositor recovery rate in the initial year is only about 35% (see Figure B.3). In contrast, in the post-FDIC period since 1992, only 20% of failures involved losses for uninsured depositors, and the average unconditional loss rate is 6%.

[12]James (1991) studies 412 bank failures between 1985 and 1988. He finds that asset losses averaged 30% for failing banks. James (1991) argues that a significant portion of these losses reflect past unrealized losses, rather than liquidation discounts. Focusing on bank failures between 1986-2007, Bennett and Unal (2015) find that the average loss amounted to 33.2% of total assets. Further, Granja et al. (2017) show that in the aftermath of the GFC, the average FDIC loss on a failed bank was around 28% of assets, with a substantial part of these losses resulting from frictions in the market for failed banks. Our evidence is broadly consistent with these papers, although we find that the recovery rates were lower in the historical, pre-FDIC sample.

3.2 Funding

Fact 2. Failing banks rely increasingly on non-core funding.

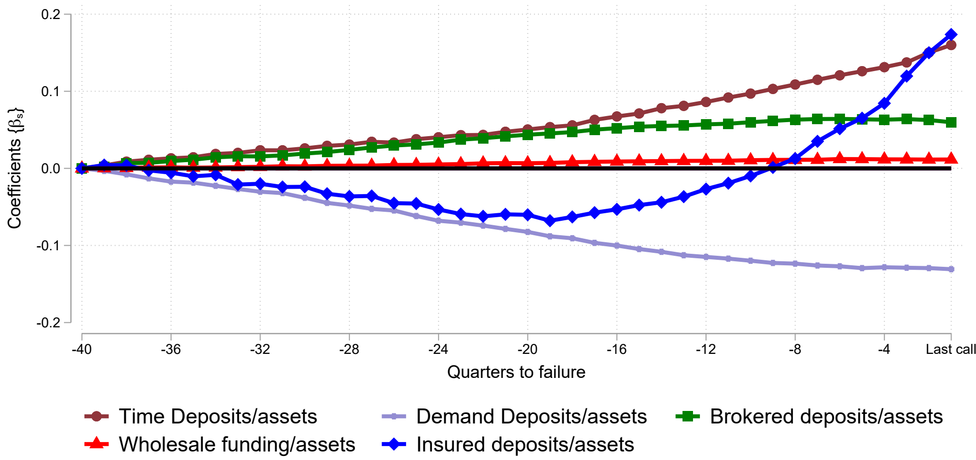
How does bank funding evolve as a bank approaches failure? Figure 3 presents the evolution of various funding ratios in the decade preceding failure. Again, we present results separately for the historical and modern samples, as the detail with which liabilities are reported changes over time.

Panel (a) of Figure 3 presents the results for the post-1959 sample. For this sample, we can distinguish between time, demand, and brokered deposits. Wholesale funding refers to the line item "other borrowed money," which pools market-based funding and funding from the Federal Home Loan Banks (FHLBs) and the Federal Reserve. In the modern sample, failing banks increasingly rely on expensive types of deposit funding. In particular, the largest increase is accounted for by time deposits, followed by brokered deposits. Rates on both time deposits and brokered deposits exhibit a higher sensitivity to changes in the federal funds rate (see, e.g., Drechsler et al., 2017) and are more sensitive to bank risk (see, e.g., Martin et al., 2023). As we show in the next subsection, these expensive sources of non-core funding are often used to finance rapid growth. In contrast, demand deposits decline as a share of assets in the decade before failure. Demand deposits, unlike time or brokered deposits, tend to be held by less price-sensitive retail investors and tend to be a cheaper source of financing. Furthermore, while smaller in absolute terms, failing banks increasingly rely on wholesale funding. Finally, in the modern sample, insured deposits actually flow into failing banks. This suggests that insured depositors do not discipline failing banks, potentially delaying failure.[13]

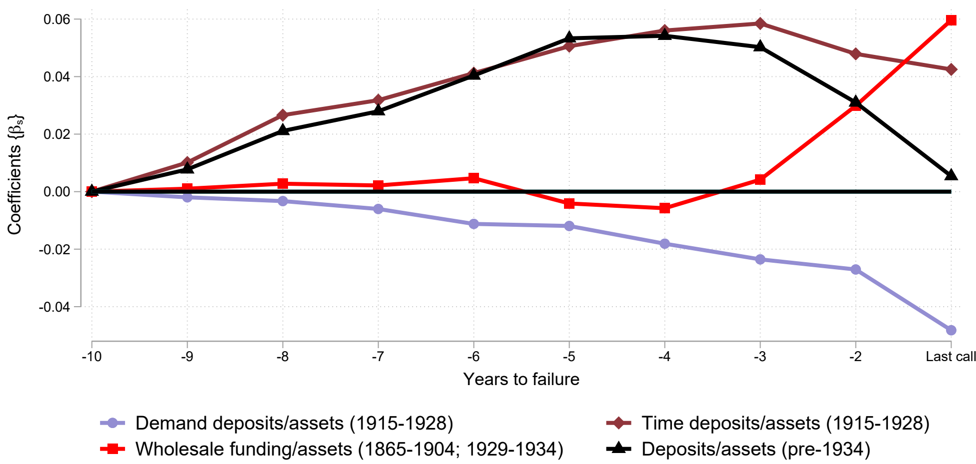
[13] These patterns are consistent with Martin et al. (2023), who find that failing banks increasingly substitute toward expensive deposit funding but also see an inflow of insured deposits before failure. The use of non-core funding to finance rapid growth is consistent with Hahm et al. (2013). Rapid growth financed by brokered deposits before failure is also a feature emphasized in previous research surveyed by FDIC (2011). The FDIC restricts borrowing through brokered deposits for banks that are not well capitalized (i.e., for adequately and undercapitalized banks). Under the FDIC brokered deposit statute dating to 1989, undercapitalized banks may not accept brokered deposits (Section 29 of the Federal Deposit Insurance Act). Given an increased chance of enforcement actions in failing banks growth of brokered deposits thus slows before failure (Martin et al., 2023).

Figure 3: *Funding of Failing Banks: 1865-2023*

(a) *1959-2023*



(b) *1865-1934*



Notes: This figure shows the sequence of coefficients from estimating Equation (1) for various funding ratios. The sample is restricted to failing banks and the ten years before they fail. In panel (a), the sample is restricted to banks that failed from 1959 through 2023. In panel (b), the sample is restricted to banks that failed from 1865 through 1934. In panel (a), wholesale funding is the amount reported in the call report line item "other borrowed money" which pools various sources of bank wholesale funding, such as advances from Federal Home Loan Banks (FHLBs), other types of wholesale borrowings in the private market, and credit extended by the Federal Reserve. In panel (b), wholesale funding is defined as the sum of "Bills Payable" and "Rediscounts." Time and demand deposits are reported separately for the 1915-1928 subsample.

Panel (b) in Figure 3 presents the evolution of funding ratios for the sample of banks that failed during 1865-1934. We observe total deposits for the entire sample and a breakdown into demand and time deposits for the 1915-1928 subsample. We proxy for wholesale funding using the line items "bills payable" and "rediscounts." Bills payable and rediscounts are forms of short-term, expensive, and secured wholesale funding. Several studies find that banks that experienced difficulties were often forced to rely on this more expensive type of funding (see, e.g., White, 1983; Calomiris and Mason, 1997; Calomiris and Carlson, 2022).

Before 1934, failing banks see an expansion of deposit funding as a share of total assets from ten to four years before failure. As in the modern period, the rise in deposits is driven by a rise in time deposits; the demand deposits to assets ratio is relatively stable. The rise in deposits relative to assets is mirrored by a fall in equity-to-assets and thus a rise in book leverage. Wholesale funding also rises at a similar pace in percentage terms, but from a lower initial share of assets.[14] However, in the two years before failure, deposit funding as a share of total assets starts to decline and is replaced nearly one-for-one by more expensive wholesale funding, likely reducing bank profitability. In the absence of deposit insurance, depositors gradually pull back from failing backs one to two years before failure.

3.3 Boom and Bust

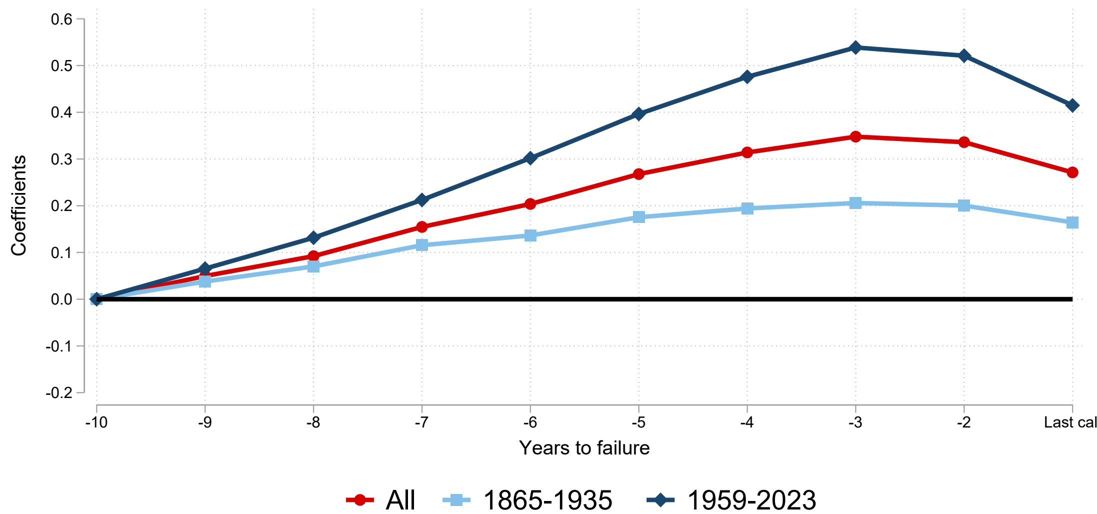
Fact 3. Failing banks follow a boom-bust pattern. They grow rapidly, both in absolute terms and relative to their peers, up to three years before they fail and then contract.

Why do banks experience gradually rising losses that eventually leads to failure? One hypothesis is that rapid loan growth leads banks to overextend themselves and incur future credit losses (Baron and Xiong, 2017; Fahlenbrach et al., 2018; Müller and Verner, 2023; Meiselman et al., 2023). Figure 4 presents results from estimating Equation (1) with

[14] Appendix Figure B.4 presents the dynamics of liabilities in logs, as opposed to as a share of assets.

the log of total assets as the dependent variable. The figure reveals that total assets in failing banks follow a boom-and-bust pattern in the decade before failure. In the full sample, assets expand by over 30% in real terms from ten years to three years before failure and then contract over the last two years before failure. Figure 4 also presents the dynamics of assets in failing banks separately for the pre-FDIC sample and the modern sample. The boom-and-bust pattern is present in both samples. However, it is significantly more pronounced in the modern period.[15]

Figure 4: ***Assets in Failing Banks: 1865-2023***



Notes: This figure reports the sequence of coefficients from estimating Equation (1) with log total assets (deflated by the CPI) as the dependent variable. The regression includes a set of bank fixed effects. The sample is restricted to failing banks and to the ten years before they fail. The sub-samples indicated in the figure legend are selected based on the years in which a bank failed.

There are several potential explanations for why the boom-bust pattern has become stronger in the modern era. First, in the historical period, bank expansions were constrained by geographic restrictions, limiting the growth of individual banks. Second, in recent decades, banks have greater access to more elastic non-core sources of funding, such as brokered deposits and funding in the Eurodollar market.[16] Third, in the historical

[15]Figure B.5 shows the estimates across finer subsamples. Asset growth prior to failure is especially large in the period leading up to the 2008 Global Financial Crisis, followed by the 1959-1981 and 1982-2006 periods.

[16]Accounts of major bank failures in the 1970s and 1980s begin to stress rapid growth financed by non-

period, national banks faced restrictions on lending against real estate, making them less exposed to real estate booms and busts, an important driver of large lending booms. Finally, the anticipation of government interventions and deposit insurance after the Great Depression may have increased risk-taking (Calomiris and Jaremski, 2019).

Which components of assets account for the overall boom in assets? Figure B.6 shows that rapid asset growth is concentrated in illiquid loans. In contrast, liquid assets such as cash and securities rise more slowly than total assets. An implication of the rapid credit expansion in failing banks is that their asset holdings tilt increasingly towards illiquid loans that are associated with higher credit risk in the decade before failure. For the modern sample, we can exploit the additional granularity of the data and decompose the expansion in lending by loan type. Figure B.7 shows that failing banks see the strongest boom in real estate lending (loans secured by real estate), followed by C&I lending. On the other hand, credit card and consumer lending are flat in real terms in the run-up to failure.

The boom-bust pattern is not simply driven by the fact that bank failures are more common at the end of a boom-bust cycle. First, the boom-bust pattern is similar for banks failing outside of major banking crises (see Figure B.8). Second, rapid asset growth predicts subsequent failure in the cross-section of banks (see Figure B.9).[17] In contrast, at short horizons, banks with lowest growth are most likely to fail.

core funding as an important factor. For example, Franklin National Bank of New York and Continental Illinois were both the largest bank failures to date at the time of their failures. These banks both underwent rapid growth financed by wholesale funding, especially from the Eurodollar market (Federal Reserve History, 2023).

[17] The relation between asset growth and future failure is stronger in the 1959-2023 sample. For the historical sample, there is a strong relation between low growth and failure within one to three years, but a weaker relation between rapid growth and failure in five to six years (see Appendix Figure B.10).

4 Predicting Bank Failures with Fundamentals

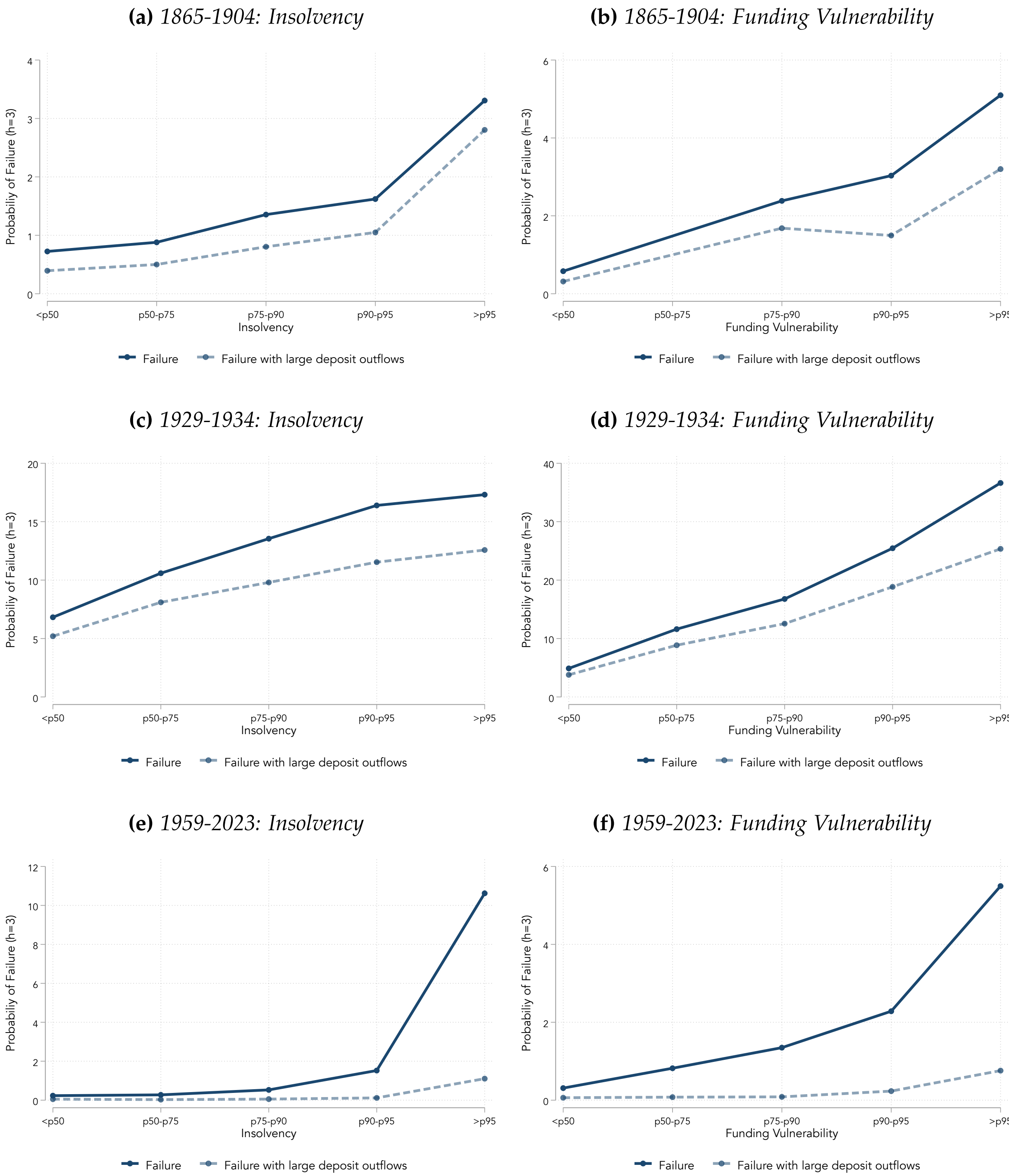
Failing banks follow systematic patterns in terms of solvency, funding, and growth in the decade before failure. The patterns are robust across different institutional settings and extend to the pre-Federal Reserve and pre-FDIC period. In this section, we study the extent to which these systematic patterns allow for the prediction of bank failures. Quantifying the predictability of bank failures based on bank fundamentals is important to establish that the patterns presented in Section 3 are not simply confounded by time trends. Moreover, the degree of predictability of bank failures is also informative about the original causes of failures, as we discuss in more detail below in Section 7.

4.1 Insolvency, Funding Vulnerability, and Failure Rates

Fundamentals and future failures. We first provide a simple visualization of the future probability of failure as a function of bank fundamentals. In Figure 5, we plot the probability of failure over the next three years ($t+1$ to $t+3$) conditional on a bank's fundamentals in year t. We consider two measures of fundamentals. The first measure is a direct proxy for a bank's risk of insolvency. This measure is meant to capture a bank's distance to default. The second measure captures a bank's funding vulnerability. This measure is meant to proxy for both the cost and "flightiness" of the funding structure, such as the reliance on non-core funding. Bank value is often generated through relying on relatively cheap deposit finance (Egan et al., 2021). In contrast, non-core funding such as wholesale deposit or non-deposit wholesale funding are expensive forms of funding and wholesale creditors are typically the most risk-sensitive investors (see, e.g., Perignon et al., 2018; Blickle et al., 2024; Cooperman et al., 2023).

The exact variables we use to measure insolvency or funding vulnerabilities in Figure 5 differ across samples due to differences in data availability. For 1865-1934, we measure insolvency by the reported undivided profits over equity. As discussed in Section 3.1,

Figure 5: ***Insolvency, Funding Vulnerability, and Future Probability of Failure***



Notes: This figure plots the probability of bank failure from $t+1$ to $t+3$ against the distribution of proxies for insolvency and funding vulnerability in year t. For the National Banking Era (1865-1904) and Great Depression (1929-1934), insolvency is measured by undivided profits over equity. As discussed in Section 3.1, this measure is a good proxy for bank income and whether bank were restricted by low net income to pay out dividends. Funding vulnerability is measured by wholesale funding over assets. For the Modern Era (1959-2023), solvency is measured by equity-to-assets, and funding vulnerability is measured by time deposits to total deposits. Failures with large deposit outflows are defined as those where deposits fall by more than 7.5% between the last call report and failure. In panels (a) and (b), failures with large deposit outflows are based on the 1880-1904 sample, as the OCC only reports deposits at the time of failure starting in 1880. In panels (e) and (f), failures with large deposit outflows are based on the 1993-2023 sample, as the FDIC only reports deposits at the time of failure starting in 1992.

this measure is a good proxy for bank income and whether banks faced restrictions in paying out dividends due to low net income. For the same period, we measure funding vulnerability by the share of wholesale funding over assets. As discussed above, this type of funding is a form of expensive, non-deposit wholesale funding. For 1959-2023, solvency is measured by equity-to-assets, and funding vulnerability is measured by time deposits to total deposits.

Before proceeding, we emphasize that the measures of insolvency and funding vulnerability are endogenous and interrelated. For example, a bank could have a more vulnerable funding structure because it is experiencing losses. In this case, while funding structure might be the best predictor of failure, the true cause of failure could nevertheless the rising losses. The measures of funding also indirectly affect solvency, as persistent reliance on expensive funding depresses bank profitability. Therefore, we do not interpret the patterns causally. Instead, the insolvency and funding vulnerability measures should both be seen as capturing weak fundamentals that are more likely to be observed in unproductive, and potentially unviable, businesses.

Figure 5 plots the relation between the future probability of failure and measures of insolvency and funding vulnerability for the National Banking Era (1880-1904), Great Depression (1929-1934), and Modern Era (1959-2023). The probability of failure over the next three years is increasing in both exposure to insolvency and funding vulnerability. The relation is generally non-linear, with the risk of failure rising rapidly in the right tails. Moving from below the 50^{th} percentile to above the 95^{th} percentile in the measure of insolvency implies an increase in the probability of failure of 3pp in the National Banking Era, and 10pp in the Great Depression and the modern era. Funding vulnerability is even more predictive of failure in the pre-FDIC data. Moving from below the 50^{th}percentile to above the 95^{th}percentile in funding vulnerability is associated with an increase in the probability of failure of 4.5pp in the National Banking Era, 31pp in the Great Depression, and 5.5pp in the modern era.

Interaction of insolvency and funding vulnerabilities. Are banks even more likely to fail when they have both weak solvency and are reliant on vulnerable funding? A bank that has weak solvency *and* has costlier and more risk-sensitive financing may see a hastier demise, as creditors raise the cost of financing or withdraw financing more quickly as losses mount (e.g., Jiang et al., 2023). Moreover, as discussed above, funding vulnerability could proxy for exposure to insolvency risk, so the combination of the two measures could provide a stronger signal of a bank at risk of failure.

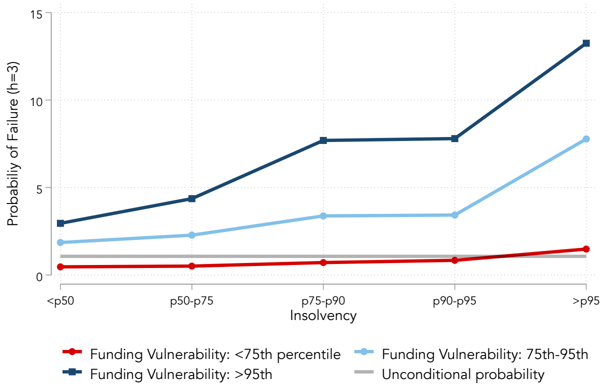
Figure 6 depicts the probability of bank failure over the next three years ($t+1$ to $t+3$) across the distribution of insolvency by whether funding vulnerability is below the 75$^{\text{th}}$ percentile, between the 75$^{\text{th}}$ and 95$^{\text{th}}$, and above the 95$^{\text{th}}$ percentile. Fundamentals are again measured in year t. The figure confirms that banks with both high insolvency risk *and* high funding vulnerability are the most likely to fail. The probability of failure for a bank that is in the top 5$^{\text{th}}$ percentile of both insolvency and high funding vulnerability is 13% in the National Banking Era, 43% in the Great Depression, and 26% in the modern era. These are large numbers, considering that the unconditional probability of failure over three years is only 0.8% in the National Banking Era, 4.2% in the Great Depression, and 1% in the modern era. Therefore, a bank with both high insolvency risk and high funding vulnerability has a 10-20 times larger probability of failure than a randomly drawn bank. Overall, this illustrates that fundamental measures of insolvency and fragile funding structure strongly predict future failure.

4.2 Performance of Fundamentals in Predicting Bank Failures

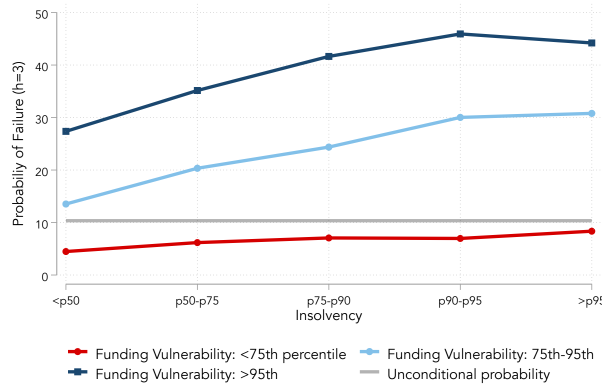
Methodology. Fundamentals are strongly associated with the future likelihood of failure. Can failures be predicted with a high degree of accuracy, that is, with a high true positive rate and a low false positive rate? We conduct a formal prediction exercise to quantify the extent to which fundamentals can predict future failures, both in- and out-of-sample.

Figure 6: ***Interaction of Insolvency and Funding Vulnerability for Predicting Future Bank Failures***

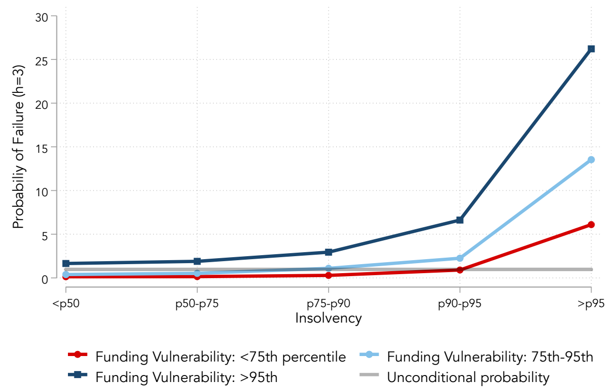
(a) *1865-1904*



(b) *1929-1934*



(c) *1959-2023*



Notes: This figure plots the probability of bank failure from $t+1$ to $t+3$ against the joint distribution of proxies for insolvency and funding vulnerability in year t. For the National Banking Era (1865-1904) and Great Depression (1929-1935), insolvency is measured by undivided profits over equity, and funding vulnerability is measured by wholesale funding over assets. For the Modern Era (1959-2023), insolvency is measured by equity-to-assets, and funding vulnerability is measured by time deposits to total deposits.

We estimate simple predictive regression models of the following form:

$$\begin{aligned}
\text{Failure}_{b,t+1\to t+h} = \alpha &+ \beta_1 \times \text{Insolvency}_{bt} \\
&+ \beta_2 \times \text{FundingVulnerability}_{bt} \\
&+ \beta_3 \times \text{Insolvency}_{bt} \times \text{FundingVulnerability}_{bt} \\
&+ \beta_4 \times \text{Growth}_{bt} \\
&+ \beta_5 \times \text{Aggregate Conditions}_t + \epsilon_{b,t+1\to t+h},
\end{aligned} \tag{2}$$

where $\text{Failure}_{b,t+1\rightarrow t+s}$ is an indicator variable that equals one if bank b fails between year $t+1$ and $t+h$. We include four sets of explanatory variables to predict failure.

First, we include bank-level outcomes that directly or indirectly measure a bank's solvency, denoted Insolvency_{bt}, at time t. These measures include measures of capitalization and exposure to losses. Second, we include bank-level measures of bank funding vulnerabilities, denoted $\text{FundingVulnerability}_{bt}$. We also consider the interaction between the insolvency and funding vulnerability measures. Again, due to differences in data availability, the exact variables we use to capture insolvency and funding vulnerability differ across samples. The exact specifications used for each sample period and the resulting regression coefficients are reported in the Appendix in Table B.6, Table B.7, Table B.8, and Table B.9.

Third, Growth_{bt} is a set of variables that capture bank-specific growth. We use five quintiles of change in log bank assets from year $t-3$ to t. This allows us to capture the non-linear relation between past growth and failure documented in Figure B.9. Fourth, for $\text{Aggregate Conditions}_{t}$, we include aggregate real GDP growth over the same three-year period. These latter two measures are available in the same form throughout the entire 1865-2023 sample. Note that we do not include bank or time fixed effects in the prediction; we only use real-time observables.

To quantify the power of these observables for predicting bank failure, we construct the receiver operating characteristic curve (ROC), a standard tool used to evaluate binary classification ability. The ROC curve traces out the true positive rate against the false positive rate as we vary the classification threshold. We then calculate the area under the ROC curve (AUC). An uninformative predictor has an AUC of 0.5, while an informative predictor has an AUC of greater than 0.5. The AUC metric is commonly used in the literature on predicting financial crises.[18] Furthermore, we test both in-sample

[18] For reference, the in-sample AUC for predicting financial crises in aggregate data based on credit and asset price growth is typically in the range 0.65-0.75 (e.g., Schularick and Taylor, 2012; Drehmann and Juselius, 2014; Baron et al., 2021; Greenwood et al., 2022; Müller and Verner, 2023). Similarly, Iyer et al. (2024) find an AUC of 0.73 when predicting local recessions with bank funding conditions.

and pseudo-out-of-sample classification performance. The pseudo-out-of-sample AUC is constructing by estimating Equation (2) iteratively on an expanding sample and predicting the probability of failure for each bank in $t+1 \rightarrow t+h$ using only data up to year t.

Main results. Table 2 presents the in-sample and out-of-sample AUC statistics based on estimating variants of Equation (2). The table reports the predictive content of various sets of variables for the National Banking Era (1880-1904)[19], Early Fed (1914-1928), Great Depression (1929-1934), and Modern Era (1959-2023). We present results for predicting failure at the 1, 3, and 5 year horizons.

Bank failures are highly predictable based on the AUC metric. The in-sample AUC for the full specification in column (4) ranges from 83% in the National Banking Era to 95% in the Modern Era. On their own, measures of insolvency and funding vulnerability both predict failures. The interaction between solvency and funding adds a significant additional boost to the predictive performance, especially in the National Banking Era, Early Fed Era, and the Great Depression. In the modern sample, where the predictability is extremely high, insolvency alone captures most of the predictive content of fundamentals.

There are several potential reasons for the stronger predictive performance in the Modern Era. First, the quality of the accounting data is higher in the Modern Era. The modern data has information on income statements, and losses are reflected more quickly through explicit accounting for NPLs and loan-loss provisioning. Second, in the historical sample, national banks with unit-branches were less diversified, implying that idiosyncratic shocks accounted for more failures. This makes these failures harder to predict. Third, in the modern sample, bank failures are preceded by larger lending booms, which often imply predictable losses down the road. Finally, the expanded government safety net can delay failure, providing more time for strong signals of failure

[19] Note that we start in 1880 as opposed to 1865 for the following reason: Further below, we also condition on deposit outflows right before failure. However, deposits in failure are only available after 1880. To allow comparability, we thus restrict all specifications to post-1880 data. Results are robust to using the 1865-1904 sample.

to be observed.

The high AUC statistics imply that bank failures can be classified with a high degree of accuracy. Figure B.11, Figure B.12, and Figure B.13 in the Appendix present a visualization of the ROC curve across models for the historical and modern samples. The ROC curve for the Modern Era implies that a forecaster willing to accept a 10% false positive rate can achieve a 85% true positive rate, again illustrating the strong predictability of bank failures.

The pseudo-out-of-sample performance is nearly as strong as the in-sample predictive performance. The high predictability also extends to longer horizons. In columns (6) and (7) we assess the predictability of bank failure over three and five-year horizons. At the five-year horizon, the in-sample AUC is nearly 80% for the historical samples, and it is even higher in the Modern Era.

Additional predictability results. The estimated coefficients for the prediction models reported in Table B.6, Table B.7, Table B.8, and Table B.9 reveal several other interesting results. Bank asset growth is significantly associated with failure. In the short-term, banks with low asset growth have the highest probability of failure. In contrast, at longer horizons of three to five years, the highest probability of failure is for banks that grow *quickly* from $t-3$ to t.[20] In fact, the relative predictive performance of the solvency versus asset growth measures switches when moving from predicting failure in the short-run to the medium run, especially in the modern sample.

Aggregate conditions also matter. Low aggregate GDP growth over the past three years is associated with a higher probability of failure in the National Banking Era and Early Fed Era. This is consistent with Gorton (1988) and Calomiris and Gorton (1991), who find that bank failures and panics in the National Banking Era were more likely following negative macroeconomic news.

[20] This holds for the National Banking Era sample (1865-1904) and the modern sample (1959-2023). However, for the Early Fed and Great Depression samples (1914-1934), banks with the lowest growth are

Table 2: *AUC Metric for Predicting Bank Failures with Fundamentals* .

Prediction horizon h	1 year					3 years	5 years
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: National Banking Era (1880-1904)							
AUC (in-sample)	0.739	0.807	0.827	0.825	0.889	0.767	0.741
AUC (out-of-sample)	0.725	0.801	0.816	0.814	0.866	0.769	0.741
N	73576	73576	73576	73392	73392	73392	73392
No of Banks	5291	5291	5291	5254	5254	5254	5254
Mean of dep. var.	.41	.41	.41	.4	.19	1.1	1.7
Panel B: Early Federal Reserve (1914-1928)							
AUC (in-sample)	0.810	0.787	0.870	0.901	0.898	0.828	0.771
AUC (out-of-sample)	0.828	0.798	0.877	0.892	0.870	0.826	0.790
N	92254	92631	92254	91865	91865	91865	91865
No of Banks	9345	9345	9345	9324	9324	9324	9324
Mean of dep. var.	.64	.63	.64	.64	.34	2.5	5.6
Panel C: Great Depression (1929-1934)							
AUC (in-sample)	0.749	0.770	0.819	0.830	0.827	0.803	0.808
AUC (out-of-sample)	0.644	0.730	0.732	0.720	0.668	0.688	0.720
N	32795	32818	32777	32702	32702	32702	32702
No of Banks	7429	7428	7428	7419	7419	7419	7419
Mean of dep. var.	3.5	3.5	3.5	3.5	2.1	9.8	12
Panel D: Modern Era (1959-2023)							
AUC (in-sample)	0.945	0.808	0.950	0.951	0.936	0.878	0.816
AUC (out-of-sample)	0.931	0.783	0.938	0.938	0.919	0.854	0.787
N	616046	614680	614680	604764	209731	604764	604764
No of Banks	22155	22152	22152	22127	14432	22127	22127
Mean of dep. var.	.26	.26	.26	.27	.035	.88	1.4
Specification details							
Insolvency	✓		✓	✓	✓	✓	✓
Funding vulnerability		✓	✓	✓	✓	✓	✓
Insolvency × Funding vuln.			✓	✓	✓	✓	✓
Growth				✓	✓	✓	✓
Deposit outflow before failure					>7.5%		
Age controls	✓	✓	✓	✓	✓	✓	✓

Notes: This table reports the area under the receiver operating characteristic curve (AUC) across different specifications, samples, and horizons using in-sample and pseudo-out-of-sample classification. The corresponding regression coefficients underlying the models for Panel A can be found in Table B.6, Panel B in Table B.7, Panel C in Table B.8, and Panel D in Table B.9. Pseudo-out-of-sample AUCs are obtained by estimating the regression model with training data from 1880-1890 (Panel A), 1914-1919 (Panel B), 1880-1904 (Panel C), and 1959-1969 (Panel D) and iteratively expanding the sample for subsequent years. Column (5) in Panel D is restricted to the years from 1993-2023 due to unavailability to deposits in failure before 1992.

5 Failures With and Without Bank Runs

Next, we focus on failures featuring bank runs and contrast these to failures without runs. We exploit that our data allows us to calculate deposit outflows immediately before failure, and we define a failure with a run as a failure featuring a large deposit outflow immediately before failure. These data allow us to ask: How large are deposit outflows right before failure? And does the predictability of bank failures differ across failures that do and do not involve runs?

5.1 Deposit Outflows in Failing Banks

Figure 7 visualizes the distribution of deposit growth immediately before failure, and Table 3 reports details on the distribution of deposit growth immediately before failure for the pre and post-FDIC samples (Panel A), as well as by specific eras (Panel B).[21] Large deposit outflows were common before the FDIC became operational but not thereafter. On average, banks experienced a 11.8% decline in deposits immediately before failure prior to the founding of the FDIC, but only a 2.3% decline after the introduction of federal deposit insurance. Deposit outflows in failing banks were highest during the Great Depression. Before the banking holiday, deposits declined by an average of 20.1% between the last call and failure. In contrast, average outflows were much more modest after the introduction of deposit insurance and have been 2% in the most recent years, a sample that includes the 2008 Global Financial Crisis.

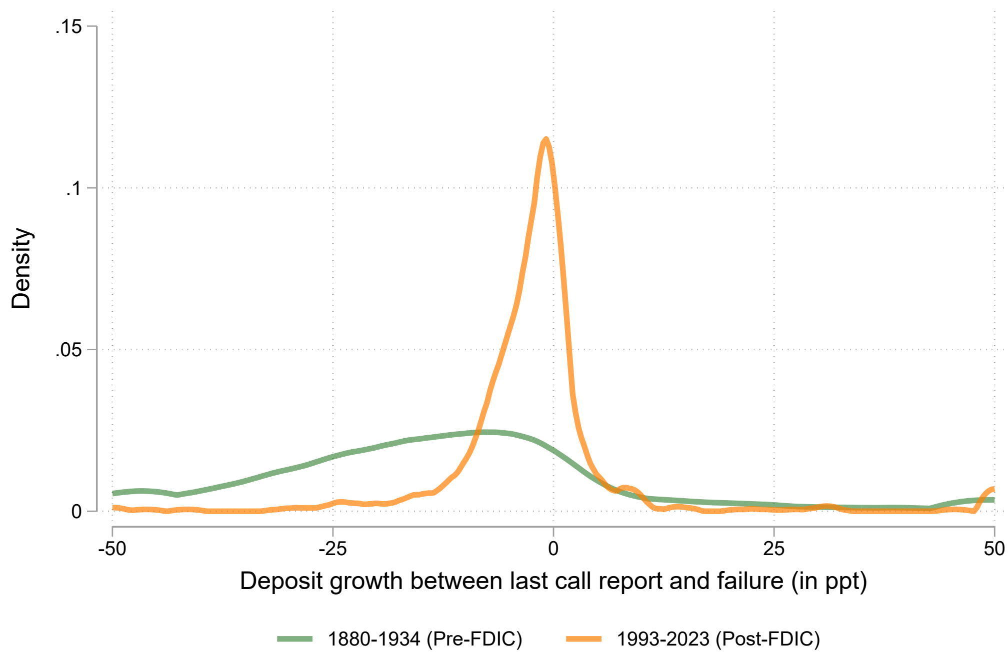
Importantly, in the historical sample, we indeed find evidence that bank failures were commonly associated with bank runs. For instance, 34% of all pre-FDIC failures were preceded by deposit outflows of more than 20%. In contrast, such large outflows are rare

also most likely to fail in five years.

[21] For the historical sample, deposits at the time of failure are the deposits recorded at suspension by the OCC. For the modern sample, deposits at failure are based on deposits at resolution reported in the FDIC Failure Transaction Database. In addition to deposits, Table B.11 shows the growth in assets between the last call report and failure. Note that the assets reported in failure are book values and can include potentially doubtful or worthless assets.

after the end of the Great Depression and only happen in 3% of all failures. However, we also find that, even before deposit insurance and when depositors had reason to expect large losses from a bank default, deposits did not always flow out of failing banks. In one-fourth of all pre-FDIC failures, deposits did not decline by more than 2.5% before failure; in 37% of all failures, deposits fell at most by 7.5%.

Figure 7: ***Deposit Outflow between Immediately before Bank Failure***



Notes: This figure shows the distribution of the growth in deposits between the last call report from before failure and the deposits reported in failure. Deposit growth is clipped at +/- 50ppt. We include failures from 1934 in the pre-FDIC sample. Even though the FDIC was founded in 1933, many receiverships in 1934 were associated with suspensions in 1933, see Appendix A.

5.2 Predictability of Failures with Large Deposit Outflows

In Figure 5, we saw that the conditional probability of failure over the next three years is increasing in measures of insolvency and funding vulnerability. Figure 5 also plots the likelihood of a failure *with a large deposit outflow* across the same bank fundamentals. We define a large deposit outflow occurring if deposits decline by more than 7.5% between the last call report and failure. The cutoff is necessarily arbitrary, but the results are

Table 3: ***Net Deposit In- and Outflows in Failing Banks Before and After the FDIC.***

Era	Average	Share of failures with deposit growth falling within...					
		<-30%	[-30,-20%]	[-20,-7.5%]	[-7.5,-2.5%]	[-2.5,0%]	>0%
Panel A: Pre versus Post-FDIC							
1880-1933 (Pre-FDIC)	-11.81	0.17	0.17	0.29	0.12	0.06	0.19
1993-2023 (Post-FDIC)	-2.26	0.01	0.02	0.12	0.28	0.33	0.29
Panel B: By Era							
1880-1913 (NB Era)	-4.68	0.20	0.13	0.18	0.07	0.03	0.40
1914-1918 (Early Fed)	-9.47	0.15	0.15	0.29	0.11	0.05	0.24
1929-1933 (Depr., pre-Hld.)	-20.12	0.23	0.27	0.33	0.08	0.03	0.06
1933-1934 (Depr., post-Hld.)	-4.88	0.03	0.05	0.31	0.28	0.17	0.16
1993-2006	-3.45	0.03	0.10	0.23	0.13	0.36	0.48
2007-2023	-2.03	0.00	0.00	0.10	0.31	0.33	0.26

Notes: This table reports the percent change in nominal deposits from the last call report before failure to the time of failure. From 1880 through 1934, deposits in failure are as reported in the OCC annual reports table on national banks in receivership. This records deposits "at date of suspension." After 1992, we use deposits in failure as reported in the FDIC's Failure Transaction Database. We further split the Depression sample into failures before and after the banking holiday in March 1933.

robust to different cutoff choices.

Figure 5 reveals that fundamentals strongly predict failures with large deposit outflows. In both the National Banking Era and the Great Depression, moving from healthy fundamentals (below the 50$^{\text{th}}$percentile) to high insolvency or funding vulnerability is associated with an increase in the probability of failure that is similar to the increase for all failures. While failures with large deposit outflows are rare in the modern sample, these failures are also associated with significantly weaker fundamentals. Thus, the failures associated with large deposit outflows—failures that likely involved runs—are not wholly unexpected events that are disconnected from fundamentals. Instead, they are consistent with depositors reacting to weak bank fundamentals and anticipating failure.

Further, we estimate Equation (2) separately for failures with large deposit outflows. Comparing columns (4), (5), and (6) in Table 2 reveals that the predictive performance of fundamentals is at least as strong for bank failures with large deposit outflows as for failures without large deposit outflows. In the National Banking Era, the in-sample AUC is 83% for all failures and 89% for failures with large deposit outflows. In the Early Fed period, the in-sample AUC is 90% both for failures with large deposit outflows and for all failures. The in-sample AUC for the Great Depression is also very similar for with and without large deposit outflows (83%). Failures with runs are thus as easy, if not easier, to predict than failures without runs. One possible reason is that the latter is more commonly associated with fraud, which is less well detected in financial statements than realized asset losses from bad investments. This finding of high predictability of failures with large deposit outflows cuts against the view that failures before the Federal Reserve or deposit insurance were unpredictable and could occur in banks without weak fundamentals due to non-fundamental runs.

5.3 Additional Evidence: OCC Cause of Failure Classification

So far we have shown that failures with large deposit outflows are predicted by deteriorating fundamentals. This suggests that deposit outflows are a consequence of weak fundamentals, rather than the ultimate cause of failure. At the same time, our empirical approach does not allow us to explicitly identify whether a bank failed because of deposit withdrawals. To reinforce the argument, it is therefore informative to consider contemporary accounts of the causes of failure.

For most national bank failures occurring between 1863 and 1937, the OCC provides the "cause of failure" identified by the bank examiner. We classify the detailed causes of failure by the OCC into seven broad categories: economic conditions, excessive lending, losses, fraud, governance issues, run, and other factors (see Appendix Table C.2 for the exact classification). While the OCC classification may contain errors or biases, it nevertheless provides insight into what examiners on the ground saw as the main cause of failure.

Figure 8 summarizes the distribution of the cause of failure for failures occurring between 1865 and 1937. The most common category is "economic conditions." This category includes failures attributed to deflation, crop loss, or a local financial depression. The second most common category is "losses." The first two categories are thus directly related to economic shocks that deteriorate a bank's asset quality. The third most common category is "fraud." In addition to facilitating risk-taking, fraud is often used to mask losses. Other common causes are "governance issues" and "excessive lending," which refers to a bank with excessive exposure to one counterparty. The most common causes of failure are thus related to deteriorating asset quality and poor fundamentals.

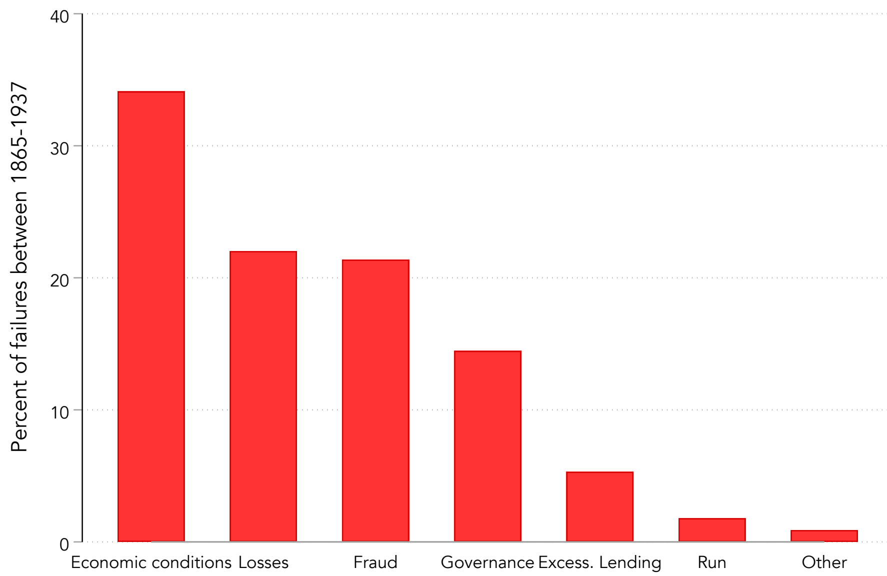
On the other hand, failures caused by runs are much less common, accounting for only a little more than 1% of all failures. "Run" covers instances where the bank was closed by a run, heavy withdrawals, and lack of public confidence. It also covers instances where the bank was closed by directors in anticipation of a run or due to rumors of a run. The limited role for runs in explaining bank failures is also consistent with the low failure rates during most of the banking "panics" of the National Banking Era, since if runs were important for explaining bank failures, one would expect large spikes in failures during "panic" years when banks faced systemic liquidity shocks.[22]

Systematic classification of the cause of bank failures by the OCC is only partial for failures that occurred during 1929-1931 and is not available for banks that failed in 1932 or 1933. Using classifications from the Federal Reserve Board of Governors, Richardson (2007) finds that, for the period 1929 through 1933, the main cause of failure of Federal Reserve member banks was asset losses, but illiquidity from heavy withdrawals also played a contributing role. The evidence from the historical sample is also consistent with a detailed study conducted by the OCC of 171 bank failures between 1979 and 1987 (Graham and Horner, 1988). That study argued that the "major cause of decline for problem banks continues to be poor asset quality that eventually erodes a bank's

[22] Calomiris and Gorton (1991) analyze the same source, but only use data from a subset of years in the pre-1914 sample in which they identified a banking panic. They find that asset losses and fraud were the predominant causes of failure during panic years. Even in banking panic years, the OCC only identified one failure due to a bank run. They concluded that "the fact that the Comptroller only attributed one failure to a bank run per se shows that the *direct* link between bank runs and bank failures during panics was not important" (Calomiris and Gorton, 1991, p. 154).

capital."[23] Poor asset quality was most often caused by poor management decisions and practices, such as imprudent lending practices, excessive loan growth, and fraud.[24]

Figure 8: ***Causes of Failure as Classified by the OCC: 1865-1937***



Notes: Causes of failure are as classified by the OCC in the tables of national banks in charge of receivers from the OCC annual report to Congress for various years. We categorize the detailed list of failure reasons as described in Appendix C.2. The classification of the causes of bank failures by the OCC is essentially complete for failures from 1865-1928, partially complete for failures from 1929-1931 and 1934-1937, and entirely missing for failures in 1932 and 1933 (see Figure C.5).

6 Fundamentals and Aggregate Waves of Bank Failures

Individual bank failures are highly predictable based on past fundamentals. In this section, we ask whether the predictability of bank failures based on fundamentals carries

[23] Graham and Horner (1988) write (also highlighted by Acharya and Naqvi (2012)): "Management-driven weaknesses played a significant role in the decline of 90 percent of the failed and problem banks the OCC evaluated. Many of the difficulties the banks experienced resulted from inadequate loan policies, problem loan identification systems, and systems to ensure compliance with internal policies and banking law. In other cases, directors' or managements' overly aggressive behavior resulted in imprudent lending practices and excessive loan growth that forced the banks to rely on volatile liabilities and to maintain inadequate liquid assets. Insider abuse and fraud were significant factors in the decline of more than one-third of the failed and problem banks the OCC evaluated... Economic decline contributed to the difficulties of many of the failed and problem banks... Rarely, however, were economic factors the sole cause of a bank's decline."

[24] Bennett and Unal (2015) find that fraud was a primary or contributing cause of failure in 24% of failures based on a sample of failures between 1989 and 2007.

over to predicting aggregate waves of bank failures during systemic banking crises.

While fundamentals may predict individual bank failures, the connection between fundamentals and failures during systemic banking crises may differ for two reasons. First, fundamentals could become less predictive of failures during crises in which many banks fail. For example, panics may decouple bank failures from fundamentals. Increased uncertainty during crises may lead creditors to withdraw even from healthy banks, breaking the cross-sectional link between weak fundamentals and failure (Chari and Jagannathan, 1988; Gorton, 1988; Allen and Gale, 1998).[25]

We find no evidence that fundamentals are less predictive of bank failures during crises. In fact, the AUC is generally higher during times of major banking crises (see Table B.10 in the Appendix). Therefore, if anything, fundamentals perform better in ranking which banks are likely to fail during crises compared to during normal times.

Second, crises may feature *excess failures* beyond what is predicted by fundamentals during normal times due to amplification mechanisms. For example, crises can feature chain reactions where bank failures lead to contagion losses for other banks through interdependent claims (Allen and Gale, 2000; Acemoglu et al., 2015) and fire sales that weaken all banks (Gertler and Kiyotaki, 2015). Amplification can also occur through contagion that leads to funding pressure for weak banks. These amplification mechanisms can increase the fundamental threshold at which banks fail, leading more banks to fail than they would otherwise.

We examine whether deteriorating fundamentals can forecast the aggregate rate of bank failures, including spikes in bank failures during systemic banking crises. We perform a pseudo-out-of-sample exercise to predict waves of bank failures as follows. Let t_0 be the first year in the sample. For each year $t > t_0 + t_{training}$, we estimate the predictive model in Equation (2) using only data from t_0 to t. As the baseline,

[25] If some depositors are informed about which banks have worse fundamentals, that will lead lower quality banks to fail. However, if all depositors are equally uninformed, then depositors cannot tell apart healthy from unhealthy banks and even banks with strong fundamentals can fail (Dang et al., 2017).

we use the model in column (4) from Table 2, namely the model with Insolvency_{bt-1}, $\text{FundingVulnerability}_{bt-1}$, their interaction, Growth_{bt}, and Aggregate Conditions_t. With this model estimated on data up until t, we predict the bank-specific failure rate in year $t+1$: $\hat{p}_{b,t+1|t}$. At time t, we thus have the pseudo-out-of-sample predicted probability of failure in $t+1$ for each bank b. We then compute the average predicted failure rate

$$\overline{p}_{t+1|t} = \sum_{b \in B_t} w_{bt} \hat{p}_{b,t+1|t},$$

where w_{bt} is the weight on bank b at time t and B_t is the set of all banks in year t.[26] We set $t_{training} = 10$ years. As in Table 2, we estimate $\overline{p}_{t|t-1}$ separately for the 1865-1904, 1905-1929, 1930-1935, and 1959-2023 samples due to differences in data availability. We weight banks equally. Results are similar when weighting banks by size.

Table 4: ***Fundamentals Predict Aggregate Rate of Bank Failures***

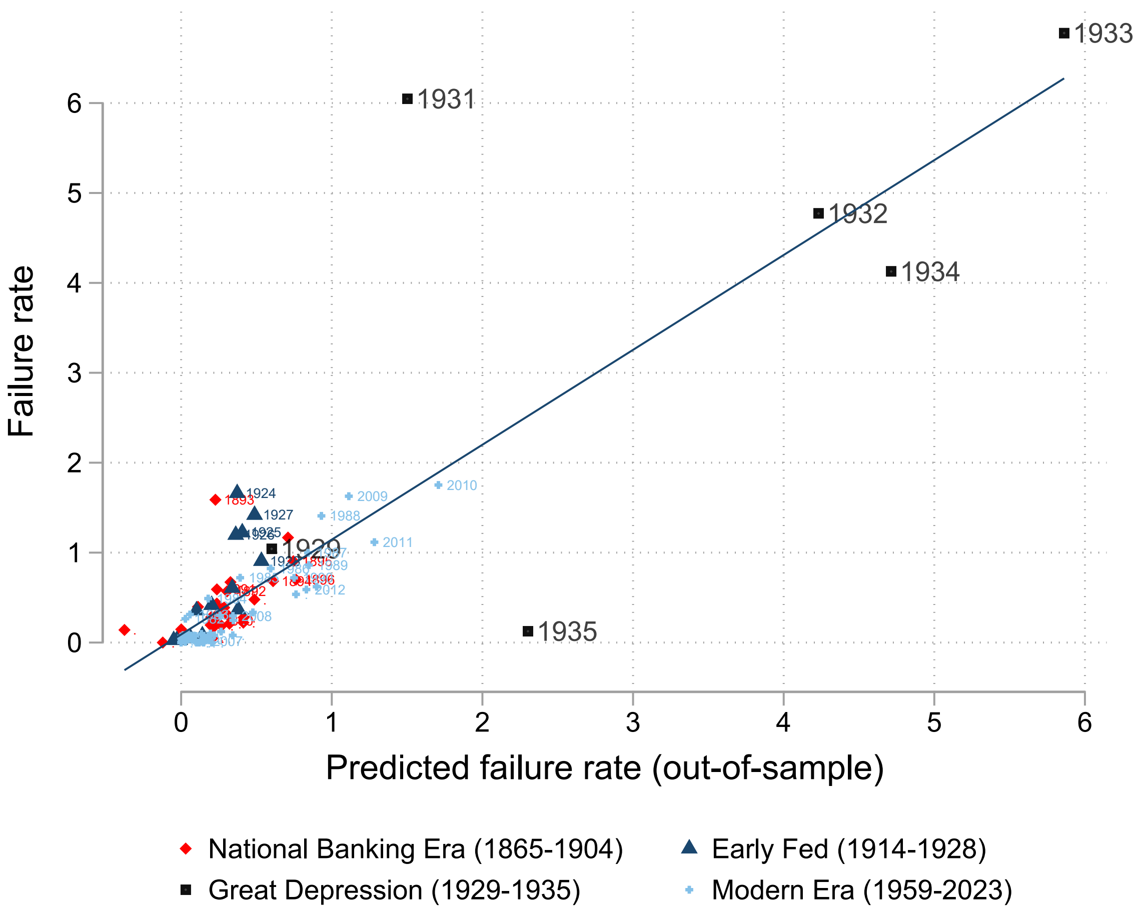
Dependent variable	Aggregate Failure Rate			
	(1)	(2)	(3)	(4)
Predicted failure rate, $\overline{p}_{t\|t-1}$	1.06***	0.79***	0.97***	1.05***
	(0.10)	(0.17)	(0.10)	(0.08)
Constant	0.09**	0.19**	0.52*	-0.03
	(0.04)	(0.08)	(0.27)	(0.02)
N	100	29	18	53
R^2	.72	.3	.66	.85
Sample	Full	1877-1905	1917-1935	1969-2021

Notes: This table presents time series regressions of the annual aggregate failure rate in year t on the average predicted failure rate $\overline{p}_{t|t-1}$. The average predicted failure rate is constructed out-of-sample using an expanding sample that only incorporates information up to year $t-1$. The predicted failure rate is based on the model in column (4) of Table 2. Appendix Table B.12 presents the predictive performance using other models from Table 2. The first observations in columns 2, 3, and 4 are for years 1877, 1917, and 1969, respectively, as we require 10 years of training data to construct the first out-of-sample prediction. Robust standard errors in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Figure 9 plots the realized aggregate failure rate against the out-of-sample predicted

[26] In a similar vein of combining information from micro-data with macro forecast variables, Banerjee et al. (2022) find that micro-level data on borrower-level repayment ability helps predict aggregate non-performing loan and bankruptcy rates.

Figure 9: ***Fundamentals Predict Aggregate Waves of Bank Failures***



Notes: This figure plots the realized aggregate failure rate against the predicted aggregate failure rate, $\overline{p}_{t|t-1}$. The predicted aggregate failure rate for year t is constructed using only information up to year $t-1$, so the prediction is pseudo out-of-sample. Both measures start 10 years after the start of our data so that we have a sufficiently long training sample. The predictions for each sample period are based on the models in column (4) of Table 2. Figure B.14 in the Appendix shows this figure separately by era. Table 4 reports the regression version of this figure for the full sample and by era.

aggregate failure rate, $\overline{p}_{t|t-1}$. Table 4 presents estimates of the corresponding time-series regression:

$$\text{FailureRate}_t = \alpha + \beta \overline{p}_{t|t-1} + u_t.$$

There is a strong positive relation between the predicted and the realized failure rate. The R^2 for the full sample is 71%. Furthermore, the estimated slope in column (1) of Table 4 is statistically indistinguishable from one, and the constant is not too far from zero. Taken at face value, this implies that crises do not feature excess failures beyond what would be predicted by deteriorating fundamentals.[27] Thus, there is strong out-of-sample predictability of aggregate bank failures based on past fundamentals. Deteriorating fundamentals matter not only for individual bank failures; they are also key to understanding widespread bank failures during the major U.S. banking crises.

Focusing on specific episodes, Figure 9 reveals that fundamentals predict waves of bank failures in the Great Depression and the 2008 Global Financial Crisis. An interesting exception is 1931, when the model substantially underpredicts the rate of failures, suggesting that amplification through contagion or fire sales could have exacerbated the rate of failures in that year. Figure B.14 and Table 4 columns (2)-(4) zoom in on specific eras. The predictability of aggregate waves of failures based on fundamentals also holds for other episodes such as the aftermath of the Panic of 1893, the 1920s, and the Savings and Loan Crisis.

The predictability of aggregate failures is especially high in the modern sample. This is likely partly due to improvements in the accounting data, which more quickly reflect bank losses. However, it may also reflect a change in the nature of bank failures. In the post-FDIC era, the timing of failure is partly determined by government supervisors, since deposit insurance can blunt market forces that would force a bank failure (Walter, 2004). Therefore, in the modern period, bank failures occur later in crises. For example, during the 2008 financial crisis, the highest rate of failures occurred in 2010, followed by 2011 and 2009.[28] In contrast, in the historical sample the timing of failure was determined

[27] We should note the caveat that the finding of a slope of one and constant of zero (indicating no excess failures) is sensitive to the exact predictive model used to construct $\overline{p}_{t|t-1}$. Appendix Table B.12 reports robustness to using different predictive models to construct $\overline{p}_{t|t-1}$. Models with a higher AUC in Table 2 perform better when predicting the aggregate failure rate. The finding of no excess failures (slope of one and constant of zero) is limited to the full model in column (4) which includes bank growth and aggregate GDP growth. This is also generally be best model based on the AUC statistics reported in Table 2. The simpler models in columns 1-3 do suggest some role for excess failures. Nevertheless, the R^2 is high for all models, consistent with the high predictive content of fundamentals.

[28] During the Savings and Loan Crisis of the 1980s, regulatory forbearance significantly delayed failure. Since Prompt Corrective Action was introduced in 1991, a critically undercapitalized bank must be closed or raise new capital within 90 days, accelerating failure for troubled banks.

by market forces, such as a run or bank owners seeking to limit their losses.

7 Relating Empirical Findings to Theories of Bank Failures

Which theories are most consistent with the empirical regularities of bank failures in the U.S. over the past 160 years? Are bank failures more commonly caused by bank runs or by deteriorating fundamentals that lead to insolvency?

We emphasize that our empirical approach does not allow us to definitively identify whether a given bank failure was caused by a bank run. Most importantly, whether a bank subject to a run would have remained solvent absent the run is an unobserved counterfactual. However, we can nonetheless make inferences about the original cause of failure by leveraging testable empirical predictions of theoretical models of bank runs. We use these predictions to assess the number of historical bank failures for which a bank run could be a plausible cause of failure and the number of failures where a bank run can be plausibly rejected as the cause of failure.

Specifically, we exploit the following three testable empirical predictions that are shared by a broad class of bank run models.

- **Predictability:** First, if a bank run is the original cause of a bank failure, the predictability of failure should at best be modest. Purely self-fulfilling panic runs as in Diamond and Dybvig (1983) should not be related to fundamentals but strike randomly (see, e.g., Gorton, 1988; Greenwood et al., 2022). Bank runs on troubled but solvent banks as in the models of Rochet and Vives (2004), Goldstein and Pauzner (2005), and He and Xiong (2012) should also only exhibit limited predictability based on information available to depositors. In these models, rational and attentive depositors run at the early signs of distress to avoid substantial losses when a bank fails. If a bank failure could be easily anticipated based on public data that is available to depositors, then depositors would act on this information and run, thus reducing predictability by triggering failure soon after the first signs of distress. Hence, for runs by attentive depositors to bring down a weak but solvent bank, a bank's predicted probability of failure before failure cannot be too high.

- **Deposit Outflows:** Second, for a bank run to represent the cause of a bank failure, deposits have to actually flow out of the bank before failure. In standard theories of bank runs, deposit outflows erode solvency by forcing banks to either liquidate their otherwise valuable assets or replace deposit funding with more expensive wholesale funding (Diamond and Dybvig, 1983; Allen and Gale, 2000; Goldstein and Pauzner, 2005). Hence, if a bank fails with only a minimal decline in deposits, deposit outflows are unlikely to have induced the bank to engage in actions that reduce solvency, so a bank run is unlikely to be the cause of failure.

- **Asset Losses in Failure:** Third, loss rates on assets held at bank failure cannot be too high when a bank run was the cause of failure (and the bank would have survived absent the run). Unlike non-financial firms, which hold mostly assets that are considerably more valuable inside a firm than outside a firm (see, e.g., Lian and Ma, 2021; Kermani and Ma, 2022), banks largely hold assets that can be separated and repossessed, such as securities and loans. OCC receivership proceedings effectively held assets to maturity to maximize the recovery rates. Hence, recovery rates on assets held in bankruptcy should be relatively high if a bank failure is caused by a bank run on an *ex ante* solvent bank. By and large, the scope of a bank run to destroy value stems from destroying a bank's franchise value, not from reducing the value of assets still held after bank closure.[29] Ma and Scheinkman (2020) estimate that the going-concern value of bank assets is only around 10-15% of assets, which

[29] The scope of bank runs to reduce the value of assets held at failure is limited, as the bank failure itself would have to substantially increase the probability of default by bank borrowers. Importantly, a bank run is unlikely to make these loans entirely worthless. As discussed in Section 3.1, the share of assets assessed as "worthless" by examiners right after a bank closed its doors correlates highly with subsequent realized losses. Thus, the majority of unrealized asset losses stem from past investment decisions for which losses seem to have been baked in before failure.

is much smaller than the going-concern value of non-financial firms (Lian and Ma, 2021). Similarly, Hirtle and Plosser (2024) estimate that the value of a bank's deposit franchise—which can be destroyed in a run (see, e.g., Drechsler et al., 2023)—is typically between 5-10% of the book value of assets. Thus, the value of a bank absent failure, while unobservable, can be approximated by the recovery value of the assets held and the going-concern value of a bank. Given that the run primarily destroys the latter, for a bank run to be a plausible cause of failure, the recovery rate on assets cannot be too low. If recovery rates are high, it would be plausible that the run destroyed the bank's franchise value, but the bank would have been solvent absent the run. In contrast, very low recovery rates would indicate that a bank was insolvent irrespective of whether a run took place or not.

In Table 5, we report the joint distribution of failures in the pre-FDIC era by predictability, deposit outflows, and asset recovery rates. We define a failure as having high predictability if the out-of-sample predicted probability of failure over the next three years right before failure is above 7.5%, modest predictability if the probability of failure is between 2.5% and 7.5%, and unpredictable if the predicted probability of failure is less than 2.5%.[30] Note that we use the out-of-sample predicted probability of failure and thus information that is in principle also available to contemporary depositors.

Further, we group banks into those that have deposit inflows before failure, modest deposit outflows of up to 7.5%, and large deposit outflows of more than 7.5% before failure.

Finally, we define a bank as having low asset losses if the recovery value of its total assets exceeds 75% throughout the receivership process, moderate losses if the recovery rate is between 50-75%, and high losses if the recovery rate is below 50%. Note that equating a recovery of 75% with having low losses is rather conservative, given that these are still considerable losses. If we assume that a bank's franchise value is somewhere

[30]Note that the cutoffs we present here are necessarily arbitrary. We report the more detailed joint distribution in Figure B.15 in the Appendix.

between 5-20%, then a bank would already be insolvent absent a run when recovery rates fall short of 80%. Table 5 presents the joint distribution for pre-FDIC failures where each of these three variable is non-missing.

Purely liquidity-driven, self-fulfilling bank runs Consider first the potential of purely self-fulfilling bank runs (e.g., Diamond and Dybvig, 1983; Peck and Shell, 2003) or shocks to the demand for liquidity (e.g., Allen and Gale, 2000) to represent a common cause of bank failures or banking crises. These types of failures should exhibit high deposit outflows, low predictability, and low asset losses in default.

Unsurprisingly, Table 3 above shows that bank runs preceding failure are not common in the modern, post-1959 sample. We find that deposit outflows before failure are modest in the Modern Era. Deposit insurance provided by the FDIC insulates a large share of depositors from a bank's solvency risk. Moreover, uninsured deposits also have low expected loss rates in the Modern Era, as shown in Table B.4. These facts have made bank runs very rare.

However, the facts presented in Table 5 also reject the notion that self-fulfilling runs on solvent banks were a common cause of bank failures even before federal deposit insurance was instituted. We find that bank failures featuring low predictability, large deposit outflows, and low losses are extremely rare. In particular, we find that only 5 failed banks (0.3% of failures) had an out-of-sample predicted failure probability over a three-year horizon of less than 2.5%, deposit outflows right before failure of more than 7.5%, and recovery rates in default of above 75%. This fact suggests that Diamond-Dybvig-style bank runs do not qualify as a plausible explanation of bank failure for the vast majority of failures in the pre-FDIC era.

Table 5: ***Number of Pre-FDIC Failures by Predictability, Deposit Outflows, and Asset Recovery Rate***

Deposit flows before failure (%)	<-7.5			[-7.5,0]			>0			Total
Asset recovery rate at failure (%)	>75	[50,75]	<50	>75	[50,75]	<50	>75	[50,75]	<50	
Predicted Pr[Fail] before failure (%)										
< 2.5	5	46	55	2	9	16	5	26	31	195
	(0.3)	(2.9)	(3.4)	(0.1)	(0.6)	(1.0)	(0.3)	(1.6)	(1.9)	(12.2)
∈ [2.5,7.5]	6	144	181	1	30	42	3	28	51	486
	(0.4)	(9.0)	(11.3)	(0.1)	(1.9)	(2.6)	(0.2)	(1.8)	(3.2)	(30.4)
∈ [7.5,20]	7	211	176	11	52	26	6	29	38	556
	(0.4)	(13.2)	(11.0)	(0.7)	(3.3)	(1.6)	(0.4)	(1.8)	(2.4)	(34.8)
>20	9	114	57	11	94	31	5	24	16	361
	(0.6)	(7.1)	(3.6)	(0.7)	(5.9)	(1.9)	(0.3)	(1.5)	(1.0)	(22.6)
Total	27	515	469	25	185	115	19	107	136	1598
	(1.7)	(32.2)	(29.3)	(1.6)	(11.6)	(7.2)	(1.2)	(6.7)	(8.5)	(100.0)

Notes: This table reports both the number and percentage (in parentheses) of bank failure by predictability, deposit outflows, and asset recovery rate. Predictability is measured as the out-of-sample predicted probability of failure over a three year horizon as of the last call report before failure. Out-of-sample predictions are taken from estimating Equation (2). The out-of-sample predicted probability of failure is obtained from the regression models reported in columns (4) of Table B.6 (1880-1904, using 1870-1880 as training data and iteratively expanding the sample for subsequent years), Table B.7 (1920-1928, using 1915-1919 as training data), Table B.8 (1929-1934, using 1870-1904 as training data). Deposit outflows are calculated as the difference between the deposits reported in the last call report and the deposits reported at failure normalized by the deposits reported in the last call report. Recovery rates are the total funds collected from assets throughout the receivership proceedings divided by the total assets held at bank failure.

Runs on troubled but solvent banks What does our evidence say about the potential for runs on solvent but troubled banks to be a common cause of bank failures?

In Section 5, we found that failures with large outflows are as easy, if not easier, to predict as those without. This fact supports the notion that runs only happen when a bank is sufficiently weak, as is suggested by theories of runs on troubled but solvent banks (see, e.g., Goldstein and Pauzner, 2005; He and Xiong, 2012). Our paper hence generalizes insights from existing empirical studies that have focused on studying specific episodes (see, e.g., Wicker, 1996; Calomiris and Mason, 1997, 2003; Iyer and Puri, 2012) and establishes that weak fundamentals are a necessary condition for a bank to fail, even the in the absence of a safety net and both conditional and unconditional on being in a financial crisis.

However, we also find that the scope for bank runs to cause the failure of troubled but solvent banks is surprisingly limited. Runs on solvent but troubled banks as in the model by Goldstein and Pauzner (2005) should exhibit low to moderate predictability, feature deposit outflows, and exhibit moderate losses in failure. However, we find that only 15% of all failures between 1880 and 1934 fulfill these criteria. In particular, Table 5 shows that only around 15% of all pre-FDIC failures featured low to modest predictability (out-of-sample predicted probability of failure of less than 7.5% over the next three years), deposit outflows, and low to moderate asset losses (a recovery rate of more than 50 cents on the dollar in receivership).

Insolvency-driven bank failures Table 5 shows that more than 80% of pre-FDIC failures were associated with a high likelihood of failure before failure (above 7.5% out-of-sample predicted chance of failure over three years), no deposit outflows, or recovery rates in receivership of less than 50%. Hence, in most bank failures, depositors either did not run at all, even when it may have been wise to do so, or they withdrew their funds from banks that were most likely already deeply insolvent. These patterns suggest that most bank failures are the result of a deterioration of a bank's solvency. Bank runs, to the extent they happen, are more commonly a consequence of imminent failure as opposed to its cause. This is not to say that the run does not matter. The bank run may determine the timing of when an insolvent bank suspends operations and the economic costs of the failure (Diamond and Rajan, 2001).

Our interpretation that insolvency, rather than runs, accounts for the preponderance of failures in the pre-FDIC era is in line with assessments of contemporary bank examiners. As we establish in Section 5.3, examiners commonly cited losses, economic shocks, or fraud, but rarely cited bank runs, as the original cause of failure.

Depositor inattentiveness before deposit insurance Table 5 further reveals that more than 57% of pre-FDIC failures have a predicted probability of failure over the next three years in excess of 7.5% in the year before failure. Further, more than a stunning 23% of all failures are associated with a predicted probability of failure exceeding 20%, which is a very high likelihood of failure for an individual bank.

As noted above, the information we use to estimate the probability of failure is public and is thus available to contemporary depositors. A bank with such a high observed probability of failure is unlikely to be viable if all depositors required fair compensation for being exposed to such a high risk of their bank failing, especially given that we find that depositor loss rates averaged 35% (see Table B.4). Figure B.16 in the appendix presents a simple calculation of the required excess return that both a risk-neutral and a risk-averse depositor would require to be compensated for such a high default risk. It shows that an annual excess rate or return above 5% would have not been uncommon for these high-risk banks. If a bank were actually forced to pay such a high deposit rate, it would arguably become unviable, as interest expenses would erode its solvency. Moreover, the high interest rate itself could be taken by depositors as a signal that the bank is in trouble. However, by construction, these banks have not failed yet. Hence, the fact that these banks have not yet failed and we as econometricians can observe such high predicted failure probabilities implies that depositors appear slow to react to the increased risk of bank failure. Bank runs, to the extent they happen, often seem to happen later than theoretical benchmarks would suggest. This finding, in turn, points to a role for behavioral frictions such as inattentive depositors or neglect of downside risk (e.g., Gennaioli et al., 2012; Jiang et al., 2023).

Theories of banking crises based on asymmetric information Our results also speak to influential theories of banking crises based on asymmetric information (see, e.g., Gorton, 1988; Chari and Jagannathan, 1988; Dang et al., 2017). Under this view, banking crises happen when depositors revise their assessment of banks' risk of failure after receiving signals about the state of the banking system or the economy. These revisions, in turn, can induce system-wide runs by uninformed creditors that cause even healthy banks to fail. Our evidence that bank failures are preceded by losses and economic downturns is consistent with the prediction of asymmetric information models that failures follow bad news. However, our findings also pose challenges to these models. In particular, we find that weak banks that end up failing can be identified quite easily among their peers using publicly available financial statements, even years before their ultimate demise and even in crises. Moreover, banking crises are substantially predictable based on weak fundamentals.

8 Conclusion

This paper studies failing banks using data on more than 37,000 banks from the United States spanning 1865-2023. Taken together, our findings suggest that most bank failures are the result of a deterioration of a bank's solvency. We find that the deterioration of solvency is typically gradual and takes place over several years. During those years, the realization of credit risk reduces income and erodes capital buffers, pushing banks slowly toward the brink of default. At times, the deterioration of a bank's solvency is preceded by a boom-phase during which failing banks likely take more risks at the margin than their peers. The erosion of a bank's profitability and capitalization ultimately results either in a bank run or a supervisory decision to close the bank, with the former being more common in the historical data. Importantly, both depositors and supervisors seem to be slow to react to information about bank fundamentals, thus making bank failures highly predictable.

We emphasize that our empirical approach does not allow us to identify the exact cause of failure. However, our evidence allows us to reject bank runs as a plausible cause of bank failure for a robust majority of at least 80% of pre-FDIC failures. Hence, our evidence suggests that bank runs on otherwise solvent banks are not a plausible common cause of bank failures for most bank failures in the history of the U.S., including the majority of pre-FDIC bank failures.

We further note that our empirical analysis focuses on bank failures, and we do not study bank runs that do not ultimately result in bank failure. Panic-based runs could, in principle, force otherwise healthy banks or banking systems to suspend convertibility of deposits into cash. Such suspensions may have helped avert failure due to cooperation through, for example, bank clearinghouses. Nonetheless, such suspensions can have adverse real economic effects, even if no bank failures follow.

Our findings have several important implications. First, a large theoretical literature explores the role of panic-based runs in increasing financial fragility. There is comparatively less work on understanding why banks experience predictable fundamental deterioration in asset values that erodes their solvency (see, e.g. Chang et al., 2024). What are the frictions that drive decisions that ultimately lead to a deterioration of bank fundamentals? Our evidence suggests that the deterioration of fundamentals is often linked to high growth in the past.

Second, the predictability of bank failures implies a role for *ex ante* interventions to prevent bank failures or mitigate their damage (Gennaioli and Shleifer, 2018). The fact that bank failures are predictable supports the active use of prompt corrective action measures, such as limiting dividend payouts and the use of non-core funding for poorly capitalized banks. More generally, our findings emphasize the importance of requiring financial intermediaries to be well-capitalized. Our findings also imply that *ex post* interventions during a crisis must address fundamental solvency issues. Policies that backstop liquidity without addressing insolvency are unlikely to be sufficient for mitigating the costs of bank failures, as recently argued by Baron et al. (2024).

Finally, our evidence on failures both before and after deposit insurance offers insights for ongoing discussions of deposit insurance reform. Before deposit insurance, failures involving large deposit outflows were common. This suggests that depositor behavior could have been important for determining the exact timing of failure. In contrast, in the modern era, deposit outflows are small, and insured deposits even flow into failing banks. This suggests important changes in the extent to which depositors discipline banks due to changes in regulation, as also suggested by Martin et al. (2023). At the same time, the high predictability of failures in the era before deposit insurance suggests that depositor discipline was, at best, imperfect. More broadly, lending booms preceding failure have increased over time, potentially consistent with increased risk-taking. While such comparisons across eras can only be suggestive, they do highlight both costs and benefits of the expansion in the government safety net.

References

Acemoglu, D., A. Ozdaglar, and A. Tahbaz-Salehi (2015). Systemic risk and stability in financial networks. *American Economic Review 105*(2), 564–608.

Acharya, V. and H. Naqvi (2012). The seeds of a crisis: A theory of bank liquidity and risk taking over the business cycle. *Journal of Financial Economics 106*(2), 349–366.

Admati, A. and M. Hellwig (2014). *The bankers' new clothes: What's wrong with banking and what to do about it*. Princeton University Press.

Allen, F. and D. Gale (1998). Optimal financial crises. *Journal of Finance 53*(4), 1245–1284.

Allen, F. and D. Gale (2000). Financial contagion. *Journal of Political Economy 108*(1), 1–33.

Alston, L. J., W. A. Grove, and D. C. Wheelock (1994). Why do banks fail? evidence from the 1920s. *Explorations in Economic History 31*(4), 409–431.

Artavanis, N., D. Paravisini, C. Robles Garcia, A. Seru, and M. Tsoutsoura (2022). One size doesn't fit all: Heterogeneous depositor compensation during periods of uncertainty. Working Paper 30369, National Bureau of Economic Research.

Banerjee, R., F. Franceschi, and S. Riederer (2022). Borrower vulnerabilities, their distribution and credit losses. *BIS Quarterly Review* (19).

Baron, M., L. Laeven, J. Pénasse, and Y. Usenko (2024). Permanent capital losses after banking crises. *Available at SSRN 3762043*.

Baron, M., M. Schularick, and K. Zimmermann (2023). Survival of the biggest: Large banks and financial crises. *Available at SSRN 4189014*.

Baron, M., E. Verner, and W. Xiong (2021). Banking crises without panics. *The Quarterly Journal of Economics 136*(1), 51–113.

Baron, M. and W. Xiong (2017). Credit expansion and neglected crash risk. *The Quarterly Journal of Economics 132*(2), 713–764.

Bennett, R. L. and H. Unal (2015). Understanding the components of bank failure resolution costs. *Financial Markets, Institutions & Instruments 24*(5), 349–389.

Berger, A. N. and C. H. Bouwman (2013). How does capital affect bank performance during financial crises? *Journal of financial economics 109*(1), 146–176.

Bernanke, B. (2018). The real effects of disrupted credit: Evidence from the global financial crisis. *Brookings Papers on Economic Activity 49*(2 (Fall)), 251–342.

Bernanke, B. S. (1983). Nonmonetary effects of the financial crisis in the propagation of the great depression. *The American Economic Review 73*(3), 257–276.

Blickle, K., M. Brunnermeier, and S. Luck (2024, 05). Who Can Tell Which Banks Will Fail? *The Review of Financial Studies 37*(9), 2685–2731.

Borio, C. E. and P. W. Lowe (2002). Asset prices, financial and monetary stability: exploring the nexus.

Calomiris, C. W. and M. Carlson (2022). Bank examiners' information and expertise and their role in monitoring and disciplining banks before and during the panic of 1893. *Journal of Money, Credit and Banking 54*(2-3), 381–423.

Calomiris, C. W. and G. Gorton (1991). The origins of banking panics: models, facts, and bank regulation. In *Financial markets and financial crises*, pp. 109–174. University of Chicago Press.

Calomiris, C. W. and M. Jaremski (2019). Stealing deposits: Deposit insurance, risk-taking, and the removal of market discipline in early 20th-century banks. *The Journal of Finance 74*(2), 711–754.

Calomiris, C. W. and J. R. Mason (1997). Contagion and bank failures during the great depression: The june 1932 chicago banking panic. *American Economic Review 87*(5), 863–883.

Calomiris, C. W. and J. R. Mason (2003). Fundamentals, panics, and bank distress during the depression. *American Economic Review 93*(5), 1615–1647.

Carlson, M., S. Correia, and S. Luck (2022). The effects of banking competition on growth and financial stability: Evidence from the national banking era. *Journal of Political Economy 130*(2), 462–520.

Chang, B., I.-H. Cheng, and H. G. Hong (2024). The fundamental role of uninsured depositors in the regional banking crisis. *Working paper*.

Chari, V. V. and R. Jagannathan (1988). Banking panics, information, and rational expectations equilibrium. *Journal of Finance 43*(3), 749–761.

Cooperman, H. R., D. Duffie, S. Luck, Z. Z. Wang, and Y. Yang (2023). Bank funding risk, reference rates, and credit supply. Working Paper 30907, National Bureau of Economic Research.

Correia, S. and S. Luck (2023). Digitizing historical balance sheet data: A practitioner's guide. *Explorations in Economic History 87*, 101475.

Dang, T. V., G. Gorton, and B. Holmström (2017). Ignorance, debt and financial crises. *Yale University and Massachusetts Institute of technology, working paper 17*.

Diamond, D. W. and P. H. Dybvig (1983). Bank runs, deposit insurance, and liquidity. *Journal of Political Economy 91*(3), 401–419.

Diamond, D. W. and R. G. Rajan (2001). Liquidity risk, liquidity creation, and financial fragility: A theory of banking. *Journal of Political Economy 109*(2), 287–327.

Drechsler, I., A. Savov, and P. Schnabl (2017). The Deposits Channel of Monetary Policy. *The Quarterly Journal of Economics 132*(4), 1819–1876.

Drechsler, I., A. Savov, and P. Schnabl (2021). Banking on deposits: Maturity transformation without interest rate risk. *The Journal of Finance 76*(3), 1091–1143.

Drechsler, I., A. Savov, P. Schnabl, and O. Wang (2023, April). Banking on uninsured deposits. Working Paper 31138, National Bureau of Economic Research.

Drehmann, M. and M. Juselius (2014). Evaluating early warning indicators of banking crises: Satisfying policy requirements. *International Journal of Forecasting 30*(3), 759–780.

Egan, M., S. Lewellen, and A. Sunderam (2021). The Cross-Section of Bank Value. *The Review of Financial Studies 35*(5), 2101–2143.

Fahlenbrach, R., R. Prilmeier, and R. M. Stulz (2018). Why does fast loan growth predict poor performance for banks? *The Review of Financial Studies 31*(3), 1014–1063.

FDIC (2011). Study on core deposits and brokered deposits. In *Submitted to Congress pursuant to the Dodd-Frank Wall Street Reform and Consumer Protection Act, Juny 8th*.

FDIC (2023). Options for deposit insurance reform. https://www.fdic.gov/analysis/options-deposit-insurance-reforms/index.html.

Federal Reserve History (2023). Continental illinois: A bank that was too big to fail.

Flood, M. D. (1998). United states historical data on bank market structure, 1896-1955. *ICPSR - Interuniversity Consortium for Political and Social Research https://doi.org/10.3886/ICPSR02393.v1*.

Friedman, M. and A. J. Schwartz (1963). *A monetary history of the United States, 1867-1960*, Volume 9. Princeton University Press.

Frydman, C., E. Hilt, and L. Y. Zhou (2015). Economic effects of runs on early "shadow banks": Trust companies and the impact of the panic of 1907. *Journal of Political Economy 123*(4), 902–940.

Gennaioli, N. and A. Shleifer (2018). *A Crisis of Beliefs: Investor Psychology and Financial Fragility*. Princeton University Press.

Gennaioli, N., A. Shleifer, and R. Vishny (2012). Neglected risks, financial innovation, and financial fragility. *Journal of Financial Economics 104*(3), 452–468.

Gertler, M. and N. Kiyotaki (2015). Banking, liquidity, and bank runs in an infinite horizon economy. *American Economic Review 105*(7), 2011–43.

Gilbert, R. A. (1986). Requiem for Regulation Q: what it did and why it passed away. *Review* (Feb), 22–37.

Goldstein, I. and A. Pauzner (2005). Demand–deposit contracts and the probability of bank runs. *Journal of Finance 60*(3), 1293–1327.

Gorton, G. (1988). Banking panics and business cycles. *Oxford Economic Papers 40*(4), 751–781.

Gorton, G. and A. Metrick (2012). Securitized banking and the run on repo. *Journal of Financial Economics 104*(3), 425 – 451. Market Institutions, Financial Market Risks and Financial Crisis.

Gorton, G. B. (2012). *Misunderstanding Financial Crises: Why We Don't See Them Coming*. Number 9780199922901 in OUP Catalogue. Oxford University Press.

Graham, F. C. and J. E. Horner (1988). Bank failure: an evaluation of the factors contributing to the failure of national banks. Proceedings 210, Federal Reserve Bank of Chicago.

Granja, J., G. Matvos, and A. Seru (2017). Selling failed banks. *The Journal of Finance 72*(4), 1723–1784.

Greenwood, R., S. G. Hanson, A. Shleifer, and J. A. Sørensen (2022). Predictable financial crises. *The Journal of Finance 77*(2), 863–921.

Grossman, R. S. (2001). Double liability and bank risk taking. *Journal of Money, Credit and Banking 33*(2), 143–159.

Grossman, R. S. (2010). *Unsettled account: The evolution of banking in the industrialized world since 1800*. Princeton University Press.

Hahm, J.-H., H. S. Shin, and K. Shin (2013). Noncore bank liabilities and financial vulnerability. *Journal of Money, Credit and Banking 45*(s1), 3–36.

Haubrich, J. G. (2020). A Brief History of Bank Capital Requirements in the United States. *Economic Commentary 2020*(05), 1–6.

He, Z. and W. Xiong (2012). Dynamic Debt Runs. *Review of Financial Studies 25*(6), 1799–1843.

Hirtle, B. and M. Plosser (2024). A measure of bank value. *Working paper*.

Huntoon, P. (2023, July). Key bank data, 1863-1935, charters 1-14348: Society of Paper Money Collectors, National Bank & National Bank Note Summary Data.

Iyer, R., S. Kundu, and N. Paltalidis (2024). Canary in the coal mine: Bank liquidity shortages and local economic activity. *Working paper*.

Iyer, R. and M. Puri (2012). Understanding bank runs: The importance of depositor-bank relationships and networks. *American Economic Review 102*(4), 1414–45.

Iyer, R., M. Puri, and N. Ryan (2016). A tale of two runs: Depositor responses to bank solvency risk. *Journal of Finance 71*(6), 2687–2726.

Jalil, A. J. (2015). A new history of banking panics in the united states, 1825–1929: construction and implications. *American Economic Journal: Macroeconomics 7*(3), 295–330.

James, C. (1991). The losses realized in bank failures. *The Journal of Finance 46*(4), 1223–1242.

Jiang, E. X., G. Matvos, T. Piskorski, and A. Seru (2023). Monetary tightening and us bank fragility in 2023: Mark-to-market losses and uninsured depositor runs? Technical report, National Bureau of Economic Research.

Jordà, O., B. Richter, M. Schularick, and A. M. Taylor (2020, 08). Bank Capital Redux: Solvency, Liquidity, and Crisis. *The Review of Economic Studies 88*(1), 260–286.

Jordà, O., M. Schularick, and A. M. Taylor (2017). Macrofinancial history and the new business cycle facts. *NBER Macroeconomics Annual 31*, 213–263.

Kermani, A. and Y. Ma (2022). Asset Specificity of Nonfinancial Firms. *The Quarterly Journal of Economics 138*(1), 205–264.

Krishnamurthy, A., S. Nagel, and D. Orlov (2014). Sizing up repo. *Journal of Finance 69*(6), 2381–2417.

Kroszner, R. S. and P. E. Strahan (2014). Regulation and deregulation of the us banking industry: causes, consequences, and implications for the future. In *Economic regulation and its reform: what have we learned?*, pp. 485–543. University of Chicago Press.

Lian, C. and Y. Ma (2021). Anatomy of corporate borrowing constraints. *The Quarterly Journal of Economics 136*(1), 229–291.

Ma, Y. and J. A. Scheinkman (2020). Going-concern debt of financial intermediaries. Working Paper 28088, National Bureau of Economic Research.

Martin, C., M. Puri, and A. Ufier (2023). Deposit inflows and outflows in failing banks: The role of deposit insurance. *Journal of Finance (Forthcoming)*.

Meiselman, B. S., S. Nagel, and A. Purnanandam (2023, August). Judging banks' risk by the profits they report. Working Paper 31635, National Bureau of Economic Research.

Metrick, A. and P. Schmelzing (2021). Banking-crisis interventions, 1257-2019. Technical report, National Bureau of Economic Research.

Mitchener, K. J. and G. Richardson (2019). Network contagion and interbank amplification during the great depression. *Journal of Political Economy 127*(2), 465–507.

Müller, K. and E. Verner (2023). Credit allocation and macroeconomic fluctuations. *Available at SSRN 3781981*.

Office of the Comptroller of the Currency (1941). *Alphabetical List of National Banks by States*. U.S. Government Printing Office.

Peck, J. and K. Shell (2003). Equilibrium bank runs. *Journal of Political Economy 111*(1), 103–123.

Perignon, C., D. Thesmar, and G. Vuillemey (2018). Wholesale funding dry-ups. *Journal of Finance 73*(2), 575–617.

Rajan, R. G. and R. Ramcharan (2016). Constituencies and legislation: The fight over the mcfadden act of 1927. *Management Science 62*(7), 1843–1859.

Reinhart, C. M. and K. S. Rogoff (2009). The aftermath of financial crises. *American Economic Review 99*(2), 466–472.

Richardson, G. (2007). Categories and causes of bank distress during the great depression, 1929-1933: The illiquidity versus insolvency debate revisited. *Explorations in Economic History 44*(4), 588–607.

Richardson, G. and W. Troost (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*(6), 1031–1073.

Rochet, J.-C. and X. Vives (2004). Coordination Failures and the Lender of Last Resort: Was Bagehot Right after All? *Journal of the European Economic Association 2*(6), 1116–1147.

Schmidt, L., A. Timmermann, and R. Wermers (2016). Runs on money market mutual funds. *American Economic Review 106*(9), 2625–57.

Schularick, M. and A. M. Taylor (2012). Credit booms gone bust: monetary policy, leverage cycles, and financial crises, 1870–2008. *American Economic Review 102*(2), 1029–1061.

Tarullo, D. (2008). *Banking on Basel: The Future of International Financial Regulation*. Peterson Institute for International Economics.

Temin, P. (1976). *Did monetary forces cause the Great Depression?* Norton.

Tufts, R. and G. Tufts (2001). Shareholder double liability and depositor losses in failed national banks: 1865–1935. *Moments in History: Office of the Comptroller of the Currency*.

van Belkum, L. (1968). *National Banks of the Note Issuing Period, 1863-1935*.

Walter, J. R. (2004). Closing troubled banks: How the process works. *FRB Richmond Economic Quarterly 90*(1), 51–68.

Wheelock, D. C. and P. W. Wilson (2000). Why do banks disappear? the determinants of us bank failures and acquisitions. *Review of Economics and Statistics 82*(1), 127–138.

White, E. (1983). *The Regulation and Reform of the American Banking System*. Princeton University Press.

Wicker, E. (1996). *The banking panics of the Great Depression*. Cambridge University Press.

Wright, D. M. and J. V. Houpt (1996). An analysis of commercial bank exposure to interest rate risk. *Fed. Res. Bull. 82*, 115.