Failing Banks

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Abstract

What causes bank failures? We create a panel covering most commercial banks from 1863 through 2023 and study the history of failing banks in the United States. We document that failing banks are characterized by rising losses, often resulting from realized credit risk. Credit losses are typically preceded by rapid lending growth, financed by non-core funding. These systematic patterns in failing banks imply that bank failures are highly predictable, even in the absence of deposit insurance, a central bank, and a wider safety net. We construct a new measure of elevated systemic risk using micro-data on bank-level fundamentals and show that it forecasts the major waves of banking failures in U.S. history. Altogether, our evidence suggests that the ultimate cause of bank failures is almost always and everywhere related to a deterioration of bank fundamentals.

JEL: G01, G21, N20, N24

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1 Introduction

Bank failures are an inherent feature of banking. In the United States, 20.2% of all national banks in existence from 1863 and 1934 and 14.5% of all commercial banks in existence from 1935-2023 failed at some point during the same period. These 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 *liquidity-driven* and result from self-fulfilling depositor panics that make otherwise healthy banks illiquid first and insolvent second, as in Diamond and Dybvig (1983). Panic runs are an important cause of bank failures in prominent accounts of the Great Depression (Friedman and Schwartz, 1963), the 2008 Global Financial Crisis (Krugman, 2016; Bernanke, 2018), and the bank failures in spring 2023.[1] An alternative view is that bank failures are caused by poor *fundamentals* such as realized credit risk, interest rate risk, governance issues, or fraud (e.g., Temin, 1976; Wicker, 1996; Calomiris and Mason, 1997; Admati and Hellwig, 2014; Gennaioli and Shleifer, 2018). The two views are not mutually exclusive. Rather, deteriorating fundamentals can make runs more likely (Allen and Gale, 1998; Morris and Shin, 1998; Goldstein and Pauzner, 2005). Importantly, however, in the first view, the ultimate cause of bank failure is the behavior of depositors, while in the latter the ultimate cause of failure is poor fundamentals.

Naturally, the question arises: Which type of failures are empirically most relevant? In particular, are bank failures primarily liquidity-driven or caused by a deterioration of

[1] The failure of Silicon Valley Bank spurred debate about whether it was caused by a Diamond-Dybvig style run. The *New York Times'* Dealbook column wrote that "The failure of Silicon Valley Bank was caused by a run on the bank. The company was not, at least until clients started rushing for the exits, insolvent or even close to insolvent." In the immediate aftermath of the failure of SVB, Justin Wolfers wrote that "it looks like a classic Diamond-Dybvig bank run." In response, George Selgin posted: "Every time a bank run happens, it gets shoe-horned into the Diamond-Dybvig theory." In an interview shortly after the failure of SVB, Douglas Diamond stated the run on SVB was "very different" from the type of run in the Diamond-Dybvig model.

fundamentals? And are bank failures predictable based on fundamentals, or does the random nature of self-fulfilling panics make most bank failures unpredictable?

Understanding the potential causes of bank failures empirically, however, is challenging. Government interventions such as deposit insurance make self-fulfilling liquidity-driven failures less likely in modern times. Thus, observed bank failures may be biased towards failures involving poor fundamentals. To overcome this challenge, we study the history of failing banks in the United States from 1863 to 2023. We construct a new database with balance sheet information for most banks in the U.S. since the Civil War. Our data consists of a historical sample that covers all national banks from 1863 to 1941 and a modern sample that covers all commercial banks from 1959 to 2023. Altogether, our data consist of balance sheets for 38,630 distinct banks, of which 6,401 fail. This rich sample thus covers a wide variety of failures across a range of institutional settings. It covers failures before and after the founding of the Federal Reserve System, the introduction of deposit insurance, the emergence of implicit guarantees such as too-big-to-fail, and modern capital regulation and supervision. Further, we capture failures of large and small banks, during and outside of downturns and systemic banking crises.

Our analysis proceeds in three steps. In the first step, we document six new facts about the dynamics of failing banks in the United States since 1863. First, failing banks follow a boom-and-bust pattern. Failing banks expand their balance sheet size via rapid loan growth up to 3 years before failure and then enter a period of decline. The boom-bust implies that banks with low growth relative to their peers are most likely to fail in the short-run. However, at longer horizons, banks with rapid growth are more likely to fail. This boom-and-bust pattern is considerably stronger in the modern sample (post-1959), after the Great Depression and the founding of the Federal Deposit Insurance Corporation (FDIC).

Second, the asset expansion in failing banks is financed by non-core funding. In both the historical and modern sample, failing banks increasingly finance their rapid expansion by relying on expensive forms of wholesale funding. For the modern era, for which more granular data are available, we further document that failing banks increasingly rely on expensive types of deposit funding, such as time deposits and brokered deposits. Demand deposits, in contrast, decline as a share of total assets.

Third, failing banks see a rise in non-performing loans and deteriorating solvency several years before failure. For the modern sample, we document a rising share of non-performing loans, declining net income, and falling equity-to-assets in the five years before failure. For the historical sample (pre-1935), we find a very similar pattern and document a steady increase in non-performing loans, a steady decline in equity-to-assets, and an increasing likelihood of regulatory restrictions on dividend payouts due to low capitalization. Our evidence thus strongly suggests that realized credit risk is a key factor for bank failures, both in modern times *and* the historical sample.

Fourth, deposit outflows immediately before failure were large before the introduction of deposit insurance, but small after the establishment of the FDIC. On its face, this suggests that depositor outflows may have been the cause of some failures in the historical sample before deposit insurance. However, our fifth fact argues against this view. From 1863 through the late 1920s, most bank failures were classified by the Office of the Comptroller of the Currency (OCC) as being caused by losses, fraud, or external shocks, such as a recession or crop failure. Despite popular narratives, runs and liquidity issues are much less commonly quoted as ultimate causes of failure according to OCC bank examiners, accounting for only 1% of classified failures.

Our sixth and final fact concerns asset recovery rates after failure. The average recovery rate on assets was less than 50% before 1935. A significant portion of these losses is likely to reflect unrealized asset losses arising before failure, rather than liquidation discounts. On average, the OCC bank examiners classified 61% of assets as "doubtful" or "worthless" right after failing banks' operations were suspended. These classifications also strongly correlate with subsequent recovery rates. Thus, even in the era when failures were preceded by large deposit outflows, most failing banks had deeply troubled assets.

In the second step, we study whether bank failures can be predicted by the systematic patterns we document in the first step. Predictability is informative about the nature of bank failures. If failures are due to non-fundamental panic runs, then failures should not be predictable by bank fundamentals. By definition, the probability of sunspot runs occurring should be unrelated to observable fundamentals (Greenwood et al., 2022). Instead, if failures are the consequence of deteriorating fundamentals, then failures can in principle be predicted based on past fundamentals.

Measures of bank fundamentals are strongly predictive of bank failures. We employ simple regression models in which we predict whether a bank will fail next year based on measures capturing bank solvency (such as bank capitalization, income, or non-performing loans), funding vulnerabilities (such as the reliance on non-core funding), and asset growth. 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 sample, before the introduction of deposit insurance in 1934, bank failures are best predicted by the combination of measures of bank solvency and funding vulnerability. We find that the AUC for predicting failure next year in the historical sample is between 80-85%. Therefore, even when purely self-fulfilling panic-based runs are in principle possible, failures are highly predictable based on bank fundamentals. After the introduction of deposit insurance, the risk of bank failure is well summarized by measures of bank solvency alone, although funding vulnerabilities also predict a higher risk of failure. In the modern sample, the predictability of bank failures is even higher, with an AUC between 90-95%.

Bank failures are also predictable at longer horizons. In the medium term, an important predictor of failure is rapid asset growth, especially in the modern sample. The role of rapid asset growth for predicting failure is consistent with credit booms setting the stage for subsequent losses (see, e.g., Fahlenbrach et al., 2018). When predicting failure in five years, the AUC is above 70% in the historical sample and 75% in the modern sample.

In the third and final step of our analysis, we examine whether micro-data on bank fundamentals can forecast waves of banking failures, including major banking crises. Isolated bank failures may be due to deteriorating fundamentals, but waves of bank failures may be due to contagion effects that cause creditors to run on healthy banks. We perform pseudo-out-of-sample forecasting exercises of individual bank failures. We then construct a new measure, *Banks-at-Risk*, that captures the share of banks with an elevated failure probability in $t+1$ using information up to year t. Intuitively, this measure captures the thickness in the right tail of distribution of the predicted failure probabilities.

The *Banks-at-Risk* measure forecasts the major waves of bank failures in both the historical sample and the modern sample. In the modern sample, the R^2 of a univariate regression of the actual bank failure rate on *Banks-at-Risk* is 90%; for the historical sample it is 75%. An important implication of this strong predictability is that spikes in bank failures during systemic banking crises cannot merely be explained by panics. Instead, both the aggregate failure rate and the cross-section of failures is strongly accounted for by deteriorating fundamentals. Nevertheless, crises do feature excess failures, beyond what is accounted for by past fundamentals, suggesting contagion could play an important amplifying role.

Altogether, our evidence suggests that bank failures are almost always and everywhere primarily related to weak fundamentals. We find that failing banks are characterized by a realization of credit losses that slowly erodes bank solvency several years before failure. For the pre-FDIC era, deteriorating solvency is especially powerful in characterizing failed banks when combined with a vulnerable funding structure.

The primacy of fundamental solvency issues for failures implies that bank failures are highly predictable. Importantly, failures are also predictable in settings where there is no lender of last resort and no deposit insurance. Thus, even during times when purely self-fulfilling runs can in theory be a plausible cause of failure, we find that fundamentals almost always play a key role. Thus, our findings challenge the empirical relevance of theories that suggest bank failures are driven by non-fundamental, self-fulfilling panic runs. The central role of fundamentals emphasizes the importance of *ex ante* interventions that increase the resilience of the financial system and reduce excessive risk-taking by banks.

Related literature. Our paper is most closely related to micro-level studies of bank failures in the United States. We are far from the first to use bank-level data to describe and predict bank failures. However, the novelty of our approach is to bring together evidence from almost 160 years of micro-level data that spans a range of institutional and regulatory regimes. This richness of the data allows us to study bank failures in environments in which self-fulfilling runs are plausible but also settings in which they are explicitly addressed by government interventions. Calomiris and Mason (2003) find that fundamentals explain bank failures in the Great Depression, rather than panic-driven depositor flight.[2] Studies using more 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). However, these studies do not analyze the dynamics of failing banks. In a large international bank-level panel, Baron et al. (2023) find that small banks are substantially more likely to fail during crises due to government rescues of large banks. Our finding that rapid asset growth predicts failure builds on Fahlenbrach et al. (2018), who show using a sample of public U.S. banks over 1974-2014 that rapid asset growth is associated with lower stock returns. Our findings on the important role of credit risk are consistent with Meiselman et al. (2023), who find that banks with high return-on-equity in good times, a proxy for high systematic risk exposure, have lower stock returns in bad times.

[2]Failures during the Great Depression were a continuation of a decade of high failure rates during the 1920s. These failures were concentrated in agricultural regions and were caused by large declines in commodity and real estate prices (Rajan and Ramcharan, 2015). For example, 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.

Second, our paper is also related to studies of aggregate credit cycles and financial crises. A large literature using country-level panel data finds that rapid growth in credit is a robust predictor of systemic banking crises (Borio and Lowe, 2002; Schularick and Taylor, 2012; Greenwood et al., 2022; Müller and Verner, 2023) and bank equity crashes (Baron and Xiong, 2017).

Third, our work also relates to studies on the nature of banking crises and the sources of bank failures and panics. 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 following risky credit booms. Gorton (1988) and Calomiris and Gorton (1991) study banking panics in the National Banking Era (1863-1913) using aggregate data and find that panics generally followed business cycle peaks and real disturbances reflected in declining in stock prices. Our paper builds on this evidence by providing micro-level evidence on the importance of deteriorating fundamentals, often following rapid lending growth, for understanding bank failures.

Roadmap. The paper proceeds as follows. Section 2 describes the data. Section 3 provides an overview of the evolution of the regulatory and institutional framework for banks in the Unites States. Section 4 provides new facts about failing banks. Section 5 presents evidence on the predictability of bank failures In Section 6, we construct a measure of systematic risk from the micro data to predict major waves of banking failures in the U.S. and section 7 concludes.

2 Data

We use two main data sources on bank balance sheets. Data on national bank balance sheets from 1863 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, and banks generally reported broad line items such as total assets, loans, deposits, and equity. Even though the OCC did not publish income statements, for most years, banks also report more granular items that allow us to measure non-performing loans and wholesale funding. Figure B.1 and Figure B.2 in the Appendix provide examples of the original source.

Data on all national banks in existence 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 by 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. 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. The OCC collected detailed information on the post-mortem developments of failing banks. This information is also recorded in the OCC's annual report.[3] 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.[4] Thus, they allow us to calculate the outflow of resources and deposits between the last call report and the failure date. 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 report the bankruptcy cost (legal expenses and salary expenses of the receiver), which allows us to estimate the recovery rate for depositors.

[3]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. For repeated observations, we use the most recent data.

[4]The data on deposits outstanding in failure are only reported starting in 1880.

Finally, until the late 1920s, the OCC also classified bank failures by their failure reason.

For the period prior to the founding of the FDIC, we rely entirely on data on national 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 financial institutions that were not chartered under federal law but state law. Between 1863 and 1935, national banks coexisted alongside state banks, trusts, and private banks. 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 Figures A.1 and A.2 in the Appendix for details on the number and market share of national banks, as well as White (1983).

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 FRS, the FDIC, and the OCC. Note that most existing research based on the Call Report usually 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 in additional information on bank charters, such as bank founding dates and primary regulator using the National Information Center (NIC) tables.

We complement the call report data with the FDIC list of failing banks. This list documents all failures of FDIC member banks from 1934 through 2023 and is available on the homepage of the FDIC. The FDIC reports, among other things, the date of failure, the amount of assets and deposits in the last available financial statement before failure, estimated loss to the FDIC, and the resolution type.

Altogether, our sample consists 38,630 unique banks.[5] Of these banks, 6,401 banks

[5]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

fail at some point throughout the sample period. Of these failing banks, 2,869 fail before 1935 and 3,515 fail after 1959. The data are at an annual frequency until 1941. After 1959, balance sheets are reported at a bi-annual frequency before becoming quarterly in 1976. Unless otherwise stated, we use annual data for our analysis to ensure comparability across different eras.

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).

3 Evolution of the U.S. Banking System

This section provides a brief overview of the U.S. commercial banking system from 1863 until 2023. We chart the evolution of banking regulation and summarize the history of bank failures and systemic banking crises. Table 1 summarizes the key institutional and regulatory features by era, and Figure 1 shows the number of failures and the failure rate throughout our sample.

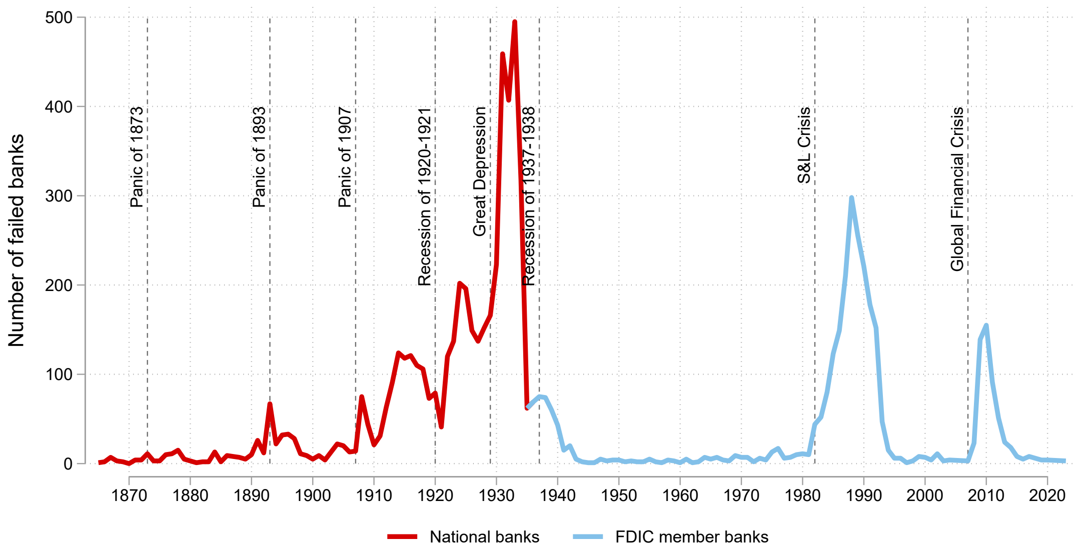
Our sample begins at the start of the National Banking Era, which spans the period between the Civil War and the founding of the Federal Reserve System (FRS), roughly 1863 to 1913. The National Banking Era emerged from reforms passed during the Civil War that allowed banks to be charted under federal law, rather than state law, as had been the case before the war. National banks issued currency backed by government bonds, which boosted demand for government debt. Other than issuing currency, national banks operated very much as banks do today, namely taking deposits and making loans.

There was relatively little government interference in banking during the National Banking Era. There was no safety net or backstop in the form of deposit insurance or

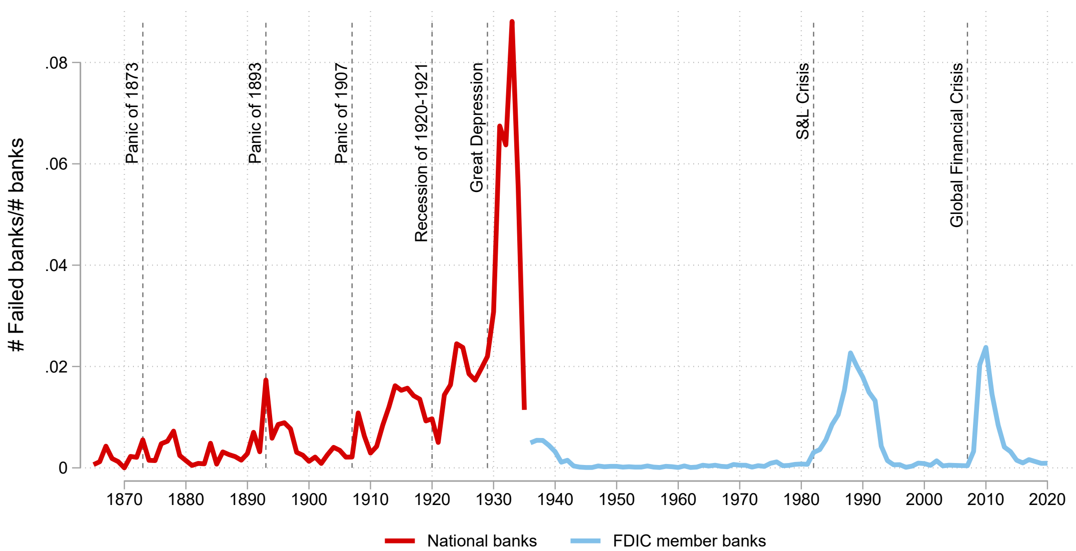
FDIC. Mechanically, this increases the total number of unique entities.

Figure 1: ***Failing Banks: 1863-2023.***

(a) *Number of failed banks*



(b) *Failure Rate*



Notes: Panel (a) plots the number of failed banks by year. Panel (b) plots the share of failed banks in the total number of banks. Vertical lines indicate selected major banking crises. The red line plots the number/rate of failing national banks, defined as national banks placed in receivership. The blue line plots the number/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.

Table 1: *Evolution of the U.S. Banking System*

Era	Years	Deposit insurance	Central bank	Capital regulation	Geographic restrictions
National Banking Era	1863-1913	No	No	$ by pop	Unit-branch**
Early Federal Reserve	1914-1928	No*	✓	$ by pop	Unit-branch**
Great Depression	1929-1935	No*	✓	$ by pop	Local branching
Boring Banking	1959-1982	✓	✓	Supervisory Discretion	Local branching
				Leverage ratio in 1985	
Deregulation and S&L	1982-2006	✓	✓	Basel I in 1989	Limited until 1994
Global Financial Crisis	2007-2015	✓	✓	Basel II/III + DFAST	No
Post-crisis	2015-	✓	✓	Basel II/III + DFAST	No

Notes: *There was no deposit insurance for national banks until the founding of the Federal Deposit Insurance Corporation (FDIC) in 1933. However, selected states implemented deposit insurance schemes for state-chartered banks already before 1933 (see Calomiris and Jaremski, 2019). ** Local branching was permitted for state banks in selected chartered states. National banks were not allowed to branch until the McFadden Act of 1927. This Act allowed national banks to branch in states in which state-chartered institutions were permitted to branch.

a central bank that could act as a lender of last resort.[6] Thus, in this period, we can be reasonably confident that bank behavior was not driven by the anticipation of government support. Capital regulation during the National Banking Era did not restrict the leverage ratio, but specified minimum dollar amounts of paid-in capital at the time of a bank's founding (Carlson et al., 2022). Thereafter, banks were able to choose their leverage freely subject to a restriction on dividends if the surplus fell below 20% of capital. National banks were restricted to operating as unit banks, which meant that each bank could only operate a single branch serving a single location. This meant that the banking system consisted of thousands of small and relatively undiversified banks (White, 1983).

The National Banking Era witnessed repeated banking crises, as seen in Figure 1. Bank failures were especially elevated in the Panic of 1893. These crises ultimately led to the creation of the Federal Reserve in 1913. The Federal Reserve could serve as a lender of last resort and had the responsibility to supervise member banks.

Despite the creation of the Federal Reserve, the 1920s saw a rise in banking failures

[6] Clearinghouses sometimes provided liquidity during panics, but these were not effective in preventing panics (Wicker, 2006). Treasury performed quasi-central bank operations toward the end of the National Banking Era, but the interventions were small (Friedman and Schwartz, 1963).

due to an agricultural depression, as well as rising urbanization that weakened the position of rural banks (Friedman and Schwartz, 1963). Figure 1 shows that the failure rate of national banks reached a new high in the 1920s. The Great Depression further exacerbated distress among banks, and the rate of bank failures spiked in the early 1930s.

The rise in failures during the Great Depression led to a wave of banking reforms. Deposit insurance was introduced in 1933 and then made permanent in 1934 with the creation of the FDIC.[7] Great Depression banking reforms also imposed a range of limits of banking activities, such as engaging in investing banking activities (Kroszner and Strahan, 2014).

In the decades after the Great Depression and WWII, banks' activities were restricted by the Depression-era regulations, and failure rates were low.[8] The period of low bank failure rates came to an end in the with a rise in bank failures in the second half of the 1970s. Bank failures further increased in the 1980s in the Savings and Loan Crisis (see Figure 1). Failures in the 1980s were driven by a combination of high interest rates, the severe recessions over 1980-1982, losses in oil and gas loans, and losses from exposure to the Latin American debt crisis.

In response to rising failures and a trend of declining bank capital ratios, the 1980s saw the introduction of regulatory capital ratios. Until the 1980s, there were no explicit capital requirements. Instead, capital regulation was conducted by supervision. This changed with the introduction of a simple leverage ratio requirement in 1985. The U.S. also implemented Basel I in 1991, introducing minimum capital requirements based on risk-weighted assets. At the same time, the 1980s also saw the deregulation of geographic restrictions on banking (Jayaratne and Strahan, 1996; Kroszner and Strahan, 2014).

[7] State level deposit insurance systems had existed before, but these became inoperative by Great Depression (Calomiris and Jaremski, 2019). State-level deposit insurance schemes did not apply to national banks.

[8] We refer to the era from 1959 through 1982 as the "Boring Banking" Era. The term "Boring Banking" is inspired by Paul Krugman, who wrote in the New York Times on April 9, 2009: "Thirty-plus years ago, when I was a graduate student in economics, only the least ambitious of my classmates sought careers in the financial world. Even then, investment banks paid more than teaching or public service - but not that much more, and anyway, everyone knew that banking was, well, boring."

The 2008 Global Financial Crisis led to a major increase in bank failures and a new wave of regulatory reform. Basel III and the Dodd-Frank Act both imposed more stringent and more complicated capital requirements. The Dodd-Frank also introduced regular stress tests for the largest banks (DFAST). The stress tests assess whether banks are sufficiently capitalized to withstand adverse scenarios.

4 Facts About Failing Banks

This section presents six new facts about failing banks. We first present facts about the dynamics of losses, leverage and liquidity in the years leading up to bank failure. We then study deposit outflows right before failure and provide details on how supervisors classified bank failures in the historical data. Finally, we study recovery rates on assets and the loss rates for depositors in failure.

4.1 Boom and Bust

Fact 1. 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.

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

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

where $y_{b,t}$ is an outcome such as the log of total assets, j measures the number of years to failure, and α_b is a bank fixed effect. We restrict the sample to failing banks that are within 10 years of failure. We also compare the dynamics of failing banks to other banks below. 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.

Figure 2 presents estimation of equation (1) with the log of total assets as the dependent variable. Total assets, like all other variables used below, are deflated by the CPI. Panel (a) in Figure 2 reveals that total assets in failing banks follow a boom-and-bust pattern in the decade before failure. Assets expand by over 30% from ten years to three years before failure and then contract over the last two years before failure.

In panel (a) of Figure 2, we also present the dynamics of assets in failing banks separately for the historical and the modern sample. The boom-and-bust pattern is present in both samples. However, it is significantly more pronounced in the modern period. Panel (b) of Figure 2 shows that 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.[9] Notably, the boom-bust pattern is not only a feature of banks failing during major banking crises. In fact, Figure A.4 reveals the pattern is similar for banks failing outside of major banking crises.

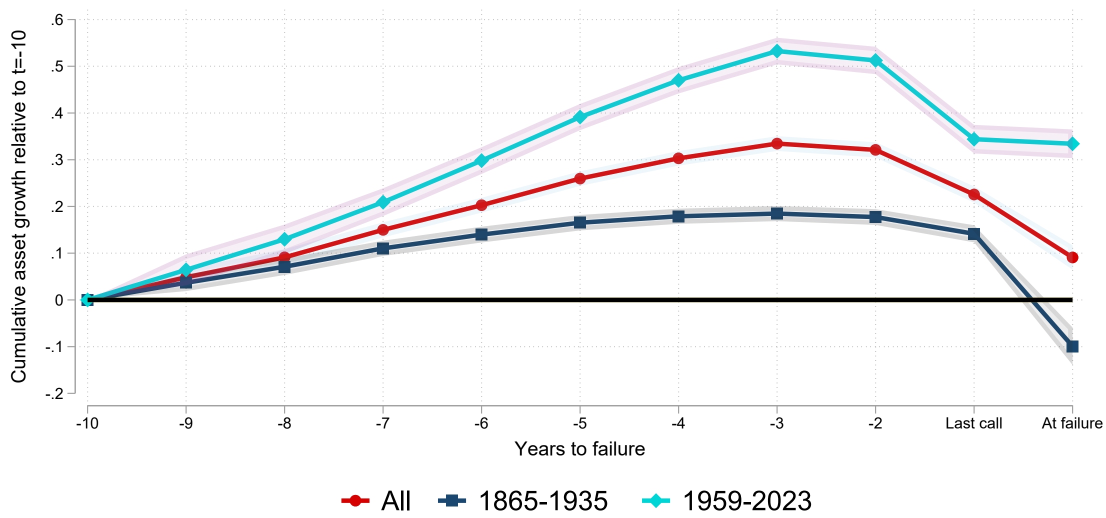
Figure 2 reveals that the timing of the decline in assets in the years immediately before failure also differ across time periods. In the modern sample, assets decline in the year before the last call. In the historical samples, there is a substantial decline in assets between the last call and failure. Below, we return to dynamics of assets and deposits in the period immediately before a bank fails.

There are several potential explanations for why the boom-bust pattern has become stronger in the modern era. First, bank expansions were constrained by geographic restrictions in the historical period, limiting the growth of individual banks. Second, the

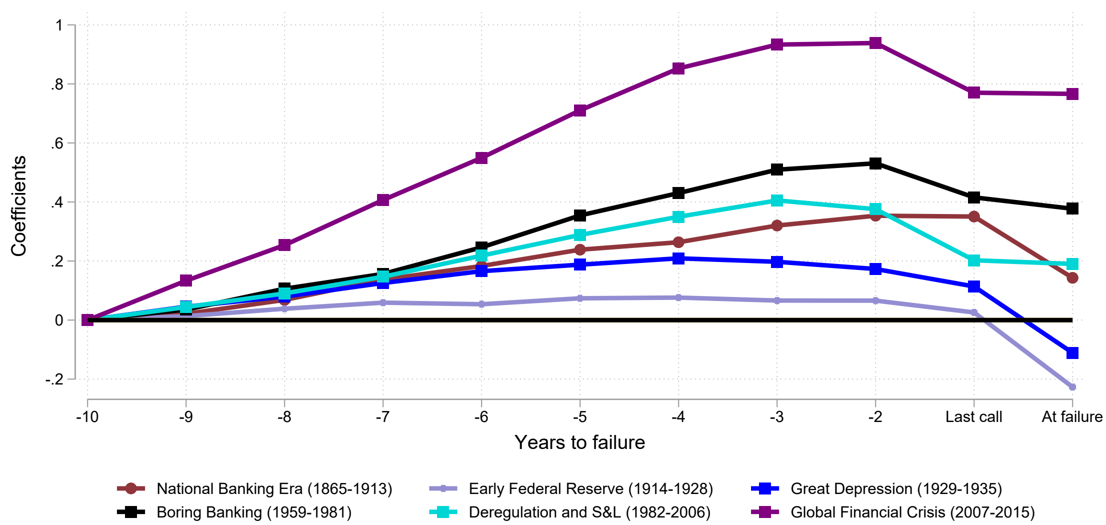
[9] Accounts of major bank failures in the 1970s and 1980s stress rapid growth as a precursor to failure. For example, Franklin National Bank of New York and Continental Illinois were both the largest bank failures to date at the time of their failure. These banks both underwent rapid growth before failing. This rapid growth is financed by wholesale funding, especially from the Eurdollar market. For example, Franklin National Bank funded its growth with Eurodollar deposits generated by the London office it had opened in 1972. Similarly, Federal Reserve History (2023) notes that Continental Illinois would not have been able to finance growth with stable retail deposits, as Illinois forbade banks from opening branches. The failure of Continental Illinois was a watershed moment due to the exceptional assistance provided by the FDIC, which moved to guarantee uninsured creditors. This led to the emergence of the concerns about "too big to fail" financial institutions.

Figure 2: ***Assets in Failing banks: 1863-2023.***

(a) *Assets growth in failing banks before and after FDIC founding*



(b) *By historical subsamples*



Notes: Both panels report the sequence of coefficients from a regression of the following form:

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

where y_{bt} is bank b's total assets (deflated by CPI), and α_b is 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 legends are selected based on the years in which a bank failed.

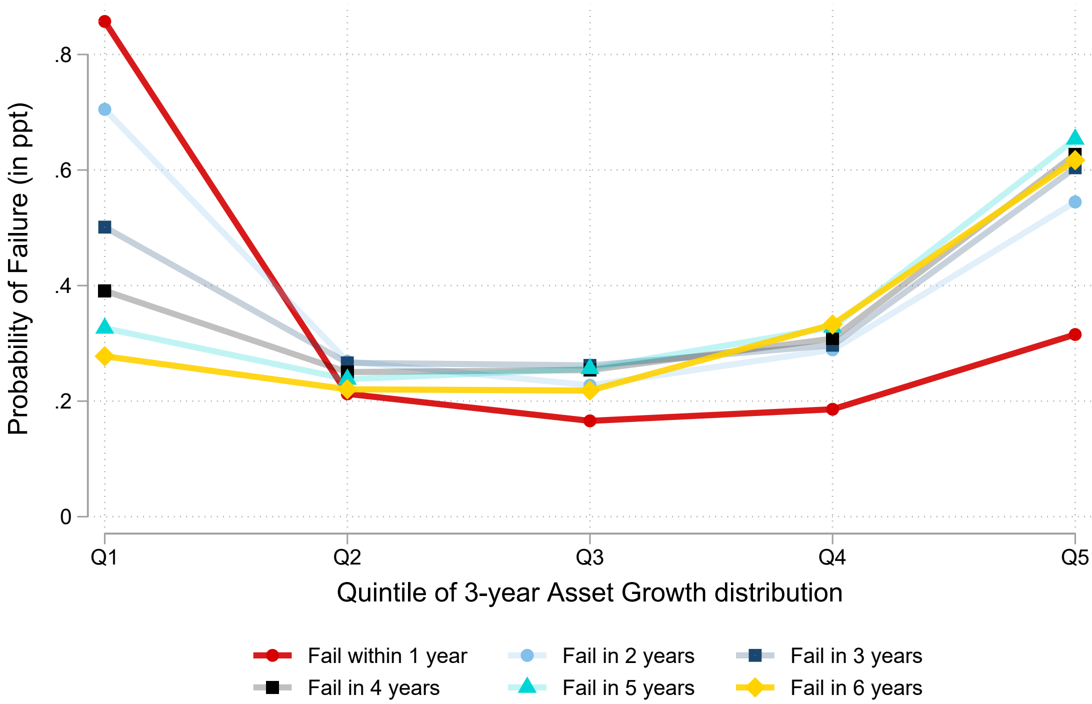
anticipation of government interventions and deposit insurance after the Great Depression may have increased risk-taking (Calomiris and Jaremski, 2019). Finally, the modern era has seen the rise of real estate finance, which in turn is associated with larger booms Jordà et al. (2016).

The evidence presented in Figure 2 does not allow one to draw conclusions on whether failing banks differ in their growth relative to their peers or whether bank failures are more common at the end of a more general boom-bust cycle. To distinguish between the two, we next examine the boom-bust pattern in the cross-section of banks. In Figure 3, we report the conditional probability of failure by quintile of the distribution of assets growth over the past three years. The red solid line shows that, at short horizons (failure within one year), banks in the lowest quintile of the asset growth distribution have a considerably higher probability of failure. For example, the probability of failure is over four times higher for banks in the lowest quintile of asset growth (0.82%) than for banks in the middle quintile of asset growth (0.16%). However, notably, banks in the highest quintile are also more likely to fail (0.3%), although not as likely as banks in the first quintile. Thus, the relation between growth and failure is U-shaped, with both slow growing and rapidly growing banks being most likely to fail.

We also report the probability of failure across the asset growth distribution at longer horizons. At intermediate horizons (failure in two to four years), the relation between failure probability and growth has an even clearer U-shape. For failure in five to six years, the probability of failure is highest for banks with the highest asset growth. The probability of failure in five years is 0.65% for banks in the top quintile of asset growth and 0.24% for banks in the middle quintile of asset growth.

In sum, there is a non-monotonic relation between growth and failure probability, with both slow and fast-growing banks being generally more likely to fail. Moreover, the relationship changes across the failure horizons considered. At short horizons, banks with lowest growth are most likely to fail. At long horizons, banks with rapid growth most likely to fail.[10] The pattern is broadly in line with failing bank being either banks that overextend themselves during a boom and then fail (Fahlenbrach et al., 2018; Meiselman et al., 2023) or banks that have a lower productivity compared to their peers and thus lose market share for a prolonged period before going out of business.

Figure 3: ***Failure Probability in the Cross-Section of Asset Growth.***



Notes: This figure plots the frequency of failure at the one to six year horizons across quintiles of the three-year asset growth distribution. Appendix Figure A.3 shows this figure separately for the pre- and post-FDIC samples.

Which components of assets account for the overall boom in assets? Figure 4 reveals that rapid asset growth is concentrated in illiquid loans. In contrast, liquid assets such as cash and securities rise more slowly than total assets. This pattern hold in both the historical and modern sample. An implication of the rapid credit expansion in failing banks is that their asset holdings tilt more and more towards illiquid loans that are associated with higher credit risk in the decade before failure.

[10]This non-monotonic intertemporal relation is substantially 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 A.3).

For the modern sample, we also exploit the additional granularity of the data and decompose the expansion in lending by loan type. Figure A.5 shows that failing banks see the strongest boom in real estate lending (loans secured by real estate), followed by C&I lending. Real estate lending rises by over 1 log point from ten years before failure to two years before failure. C&I lending rises by 0.78 log points. On the other hand, credit card and consumer lending are essentially flat in real terms. These dynamics in the bank-level data are consistent with aggregate evidence that systemic banking crises are often preceded by rapid mortgage and real estate-based lending (Jordà et al., 2016; Müller and Verner, 2023).

4.2 Funding

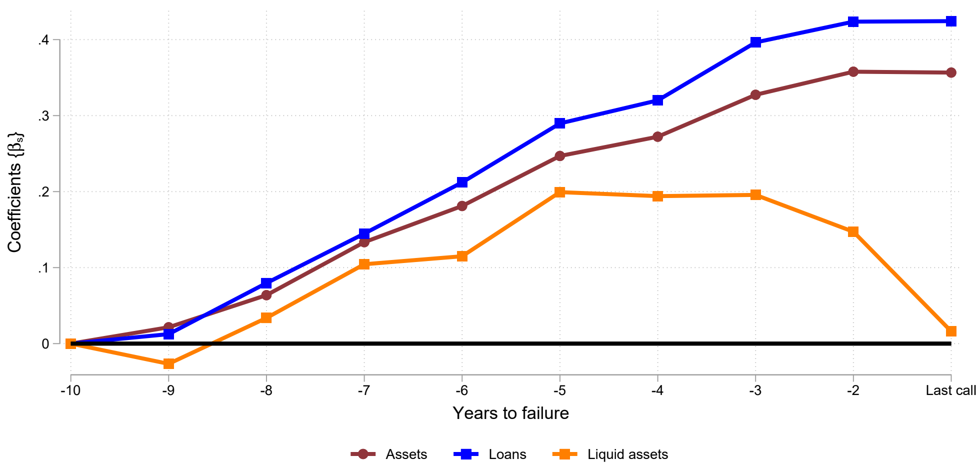
Fact 2. Asset growth is financed by non-core funding.

How is the asset expansion in failing banks financed? And how does bank funding evolve as a bank approaches failure? The detail with which liabilities are reported differs significantly across the historical and the modern sample. Therefore, we present results on the dynamics of funding in failing banks separately for different time periods.

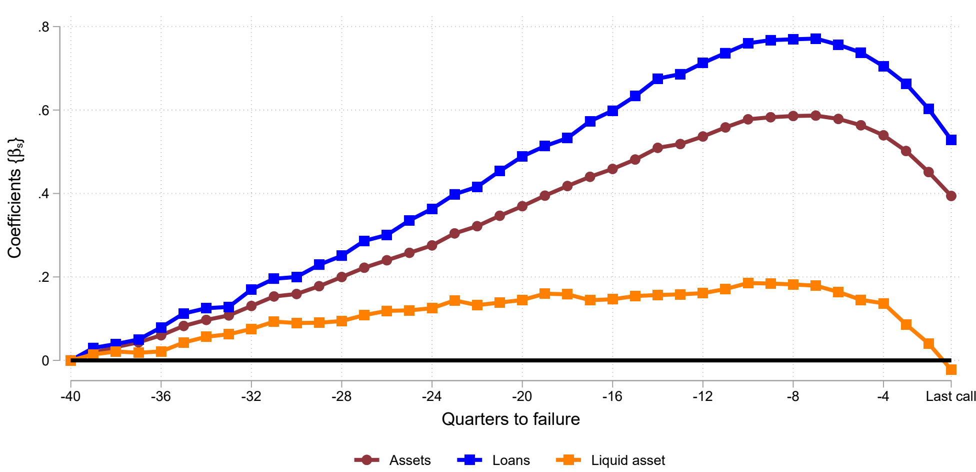
Panel (a) in Figure 5 shows results from estimating Equation (1) using regular deposits/assets, interbank deposits/assets, and wholesale funding/assets as the dependent variable and restricting the sample to banks that failed before 1904. For the historical sample, we observe total deposits, but we cannot consistently distinguish between different types of deposits. We proxy for wholesale funding by using the line items "bills payable" and "rediscounts." Bills payable and rediscounts are forms of short-term, expensive, secured wholesale funding. Banks typically used this form of funding to meet a surge in demand for funds, such as processing the autumn crop harvest. However, several studies have also found that banks that experienced difficulties relied on this type of expensive funding more permanently (see, e.g., White, 1983; Calomiris and Mason, 1997; Calomiris and Carlson, 2022; Carlson et al., 2022).

Figure 4: ***Liquid and Illiquid Assets in Failing Banks***

(a) *Before 1935*



(b) *After 1959*



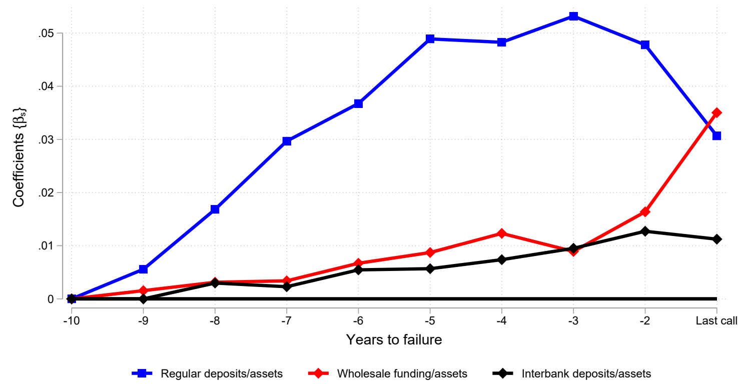
Notes: Both panels show the sequence of coefficients from a regression of the following form:

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

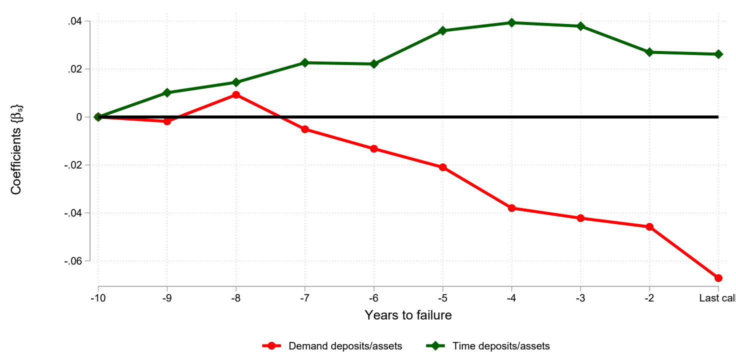
where y_{bt} is the logarithm of either assets, loans, or liquid assets (all deflated by CPI). α_b is a set of bank fixed effects. The sample is restricted to failing banks and to the ten years before they fail. From 1863 through 1941, we define liquid assets as the sum of currency, checks, legal tender, interbank claims, bond to secure deposits and bond on hand, bills of national banks and state banks. From 1959 onwards, liquid assets are defined as currency and reserves held, balances with other banks, cash items in collection, and security holdings (both government-issued and private label).

Figure 5: ***Funding of Failing Banks***

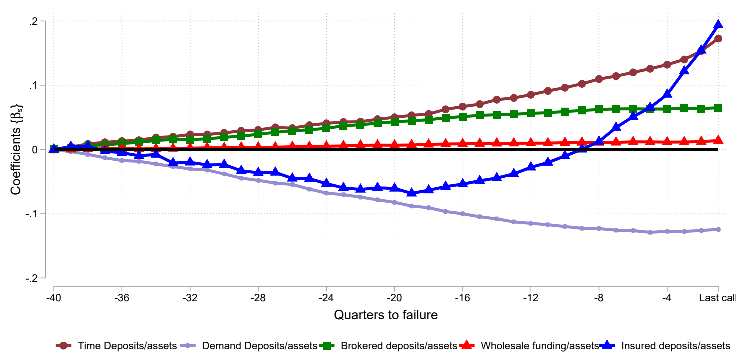
(a) *1863-1904*



(b) *1905-1928: Time and Demand Deposits*



(c) *1959-2023*



Notes: Both panels show the sequence of coefficients from estimating Equation (1) for various funding ratios. The sample is restricted to failing banks and to the ten years before they fail. In panel (a), the sample is restricted to data from 1863 through 1904, in panel (b) to data from 1905-1928, and in panel (c) to data from 1959 through 2023. Due to changes in the detail with which liabilities are reported, we exclude the period 1929-1935 from panel (b); see Figure A.6 for an analysis of wholesale funding and deposit funding for banks that failed in the period 1929-1935. In panel (a) wholesale funding is defined as the sum of "Bills Payable" and "Rediscounts". In panel (b), 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.

Before 1904, failing banks see an expansion of deposit funding as a share of total assets from ten to five years before failure. Wholesale funding also rises as a similar pace in percentage terms, but from a lower initial share of assets.[11] This rise in deposits and wholesale funding relative to assets is mirrored by a fall in equity-to-assets and thus a rise in leverage. Notably, 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 appear to pull back from failing backs one to two years before failure. The decline in deposits in the two years before failure, however, is small compared to the outflow of deposits in the final months before failure in the sample before deposit insurance, as we document below.

Panel (b) of Figure 5 presents the evolution of demand deposits and time deposits as a share of total deposits in the 1905-1928 sample. In this period, the OCC balance sheets on national banks separately report demand and time deposits. We see that time deposits as a share of total deposits rises by nine percentage points in the decade before failure, while demand deposits decline.[12]

Panel (c) of Figure 5 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 FHLBs and the Federal Reserve.

In the modern sample, failing banks finance their expansion using 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 typically 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., 2022)

[11] Appendix Figure A.7 presents the dynamics of liabilities in logs, as opposed to as a share of assets.

[12] Figure A.6 presents the evolution of wholesale funding and deposit funding for banks that failed in the period 1929-1935. Similar to the 1863-1904 sample, failing banks see an outflow of deposits and an increasing reliance on more expensive wholesale funding.

and thus represent a more expensive type of funding. 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. Wholesale funding also increases sharply right before failure (see Figure A.7 panel (b)).

This evidence is broadly consistent with the observation that, during lending booms, traditional retail (core) deposit funding is supplemented with other (non-core) sources of funding in order to finance rapid asset expansion (Hahm et al., 2013). Indeed, the transition toward greater access to non-core funding sources since the 1970s is another reason for the more pronounced boom-bust pattern in failing banks in the modern era. Rapid growth financed by brokered deposits before failure is also a feature emphasized in previous research surveyed by FDIC (2011).[13] In line with this evidence, Martin et al. (2022) find that failing banks increasingly substitute toward expensive deposit funding.

4.3 Losses and leverage dynamics

Fact 3. Failing banks see rising losses and deteriorating solvency before failure.

We next examine the dynamics in indicators of loan losses and solvency. Modern financial statements allow us to measure loan losses directly from balance sheets as banks are required to classify non-performing loans (NPLs) and provision for losses in their income statement. For the pre-1935 sample, however, equivalent measures are not available. For instance, national banks were not required to provision for loan losses. As a consequence, their income and hence their equity-to-assets ratio were not immediately impacted when loans became non-performing. Thus, changes in the observed equity-to-assets ratio were mostly governed by changes in assets. Nonetheless, the reported

[13] Moreover, 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).

line items allow us to construct proxies for non-performing loans and losses. The main proxy is the balance sheet item "Other Real Estate Owned" (OREO). This item reflects collateral seized and held on balance sheet, usually following foreclosure.[14] In Appendix Figure A.10, we document that OREO as share of loans for failing banks immediately before failure is strongly positively correlated with the share of assets classified as doubtful or worthless by the OCC in failure.

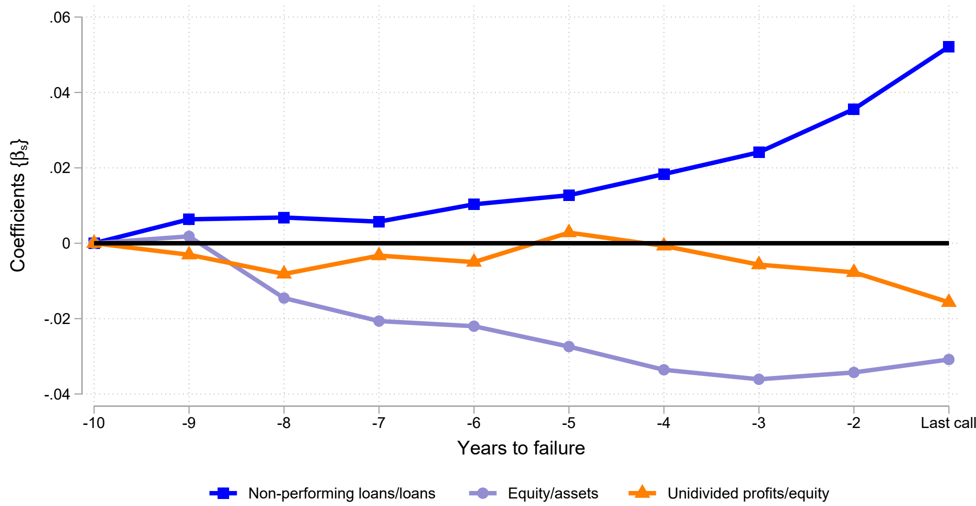
In addition, we exploit details on capital regulation in the National Banking Act. Bank equity was accounted for in three balance sheet line items: capital paid-in, surplus fund, and undivided profits. A bank's paid-in capital was determined by the population at the founding of the bank. Before a bank was able to pay out dividends, it had to have at least 20% of their paid-in capital in its surplus funds (White, 1983). We proxy restrictions to pay out dividends due to low capitalization by the ratio of undivided profits listed on the balance sheet falling short of either 1% or 2.5% of total bank equity.

Figure 6 illustrates the evolution of these proxies for losses in the pre-1935 sample. In the decade before failure, failing banks see an increase in several measure of loan losses. First, panel (a) shows that non-performing loans (OREO) as a share of total loans rises, especially in the five years preceding failure. Second, undivided profits relative to equity declines. Panel (b) shows that the share of banks listing any non-performing loans rises by 50 percentage points. Further, there is a 25-percentage point increase in the likelihood that a bank is restricted from paying out dividends because its undivided profit balance is too low. Hence, for the historical sample, we find that failing banks were likely to experience rising losses many years before failure. Finally, the ratio of equity to assets declines. But as noted above, this decline is mostly driven by the expansion of assets as the majority of bank equity comes from paid-in capital, which was typically

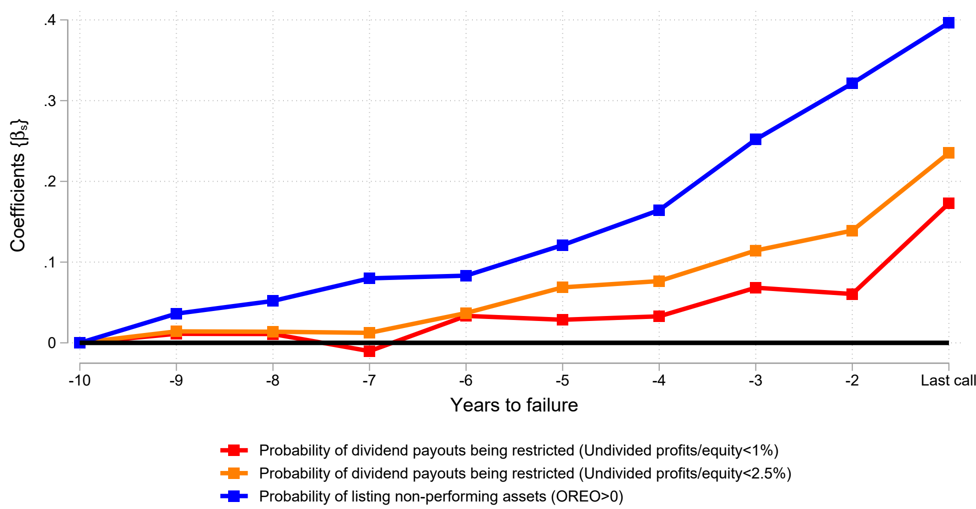
[14] OREO typically refers to real estate property assets that a bank holds, but that are not part of its business. Often, these assets are acquired due to foreclosure proceedings and are comparable to seized collateral. Note that OREO also pools collateral seized or acquired in foreclosure proceeds with other real estate the banks may have as part of relocation of banking premises. We therefore verify that it is correlated with actual losses in failure.

Figure 6: ***Losses and Leverage of Failing Banks: Pre 1935***

(a) *Pre 1935: Equity and Non-Performing Loans*



(b) *Pre 1935: Non-Performing Loans and Dividend Payout Restrictions*



Notes: Both panels show the sequence of coefficients from a regression of the following form:

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

where y_{bt} is the ratio indicated in the figure legends and α_b is a set of bank fixed effects. The sample is restricted to failing banks and to the ten years before they fail and between 1863 and 1904.
Non-performing loans are proxied for by the line item "Other real estate owened (OREO)." Figure A.10 shows that OREO listed in the last call before failure is strongly correlated with assets classified as doubtful or worthless in failure by the OCC. Restrictions on dividend payouts are proxied for by the share of undivided profits of total equity falling short of 2.5%.

time-invariant.

Figure 7 presents evidence for the post-1959 sample. Between ten and five years before failure, measures of losses and net income are flat. Thus, even though failing banks undergo a boom in assets, as shown above, the credit expansion does not result in higher returns on assets. However, starting five years before failure, there is a gradual rise in non-performing loans. In the five years up to failure, NPLs rise over 10 percentage points in failing banks. This rise in NPLs translates into rising loan loss provisions, which translates into 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.

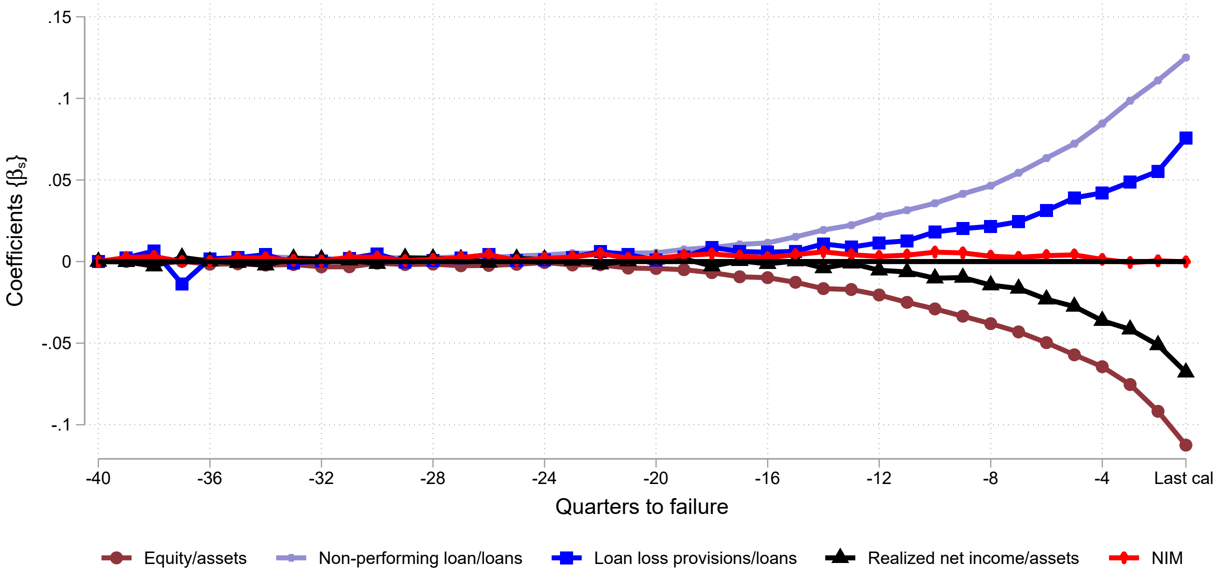
Figure 7 also plots the evolution of the net interest margin. Interestingly, the net interest margin is stable in the run-up to failure. In the Appendix in Figure A.11 we show that failing banks both experience higher interest income (indicating higher risk taking) but also higher interest expenses (in line with higher reliance on expensive forms of funding). Abstracting from valuation effects on holding on 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 interest-insensitive deposit finance (Drechsler et al., 2021). Instead, the patterns in Figure 6 and Figure 7 suggest that failures are mainly associated with realized credit risk.

4.4 Deposit Outflows Immediately Before Failure

Fact 4. Deposit outflows immediately before failure were large before 1935 but not after the introduction of deposit insurance.

We next study the evolution of deposits in the period immediately before failure. Figure 8 shows the difference (in percent) between the deposits reported in the last call

Figure 7: ***Losses and Leverage of Failing Banks: 1959-2023***



Notes: The figure shows the sequence of coefficients from a regression of the following form:

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

where y_{bt} is the ratio indicated in the figure legends, and α_b is a set of bank fixed effects. The sample is restricted to failing banks and to the ten years before they fail and banks that fail after 1959. The net interest margin (NIM) is defined as the difference of total interest income net of interest expenses normalized by total assets.

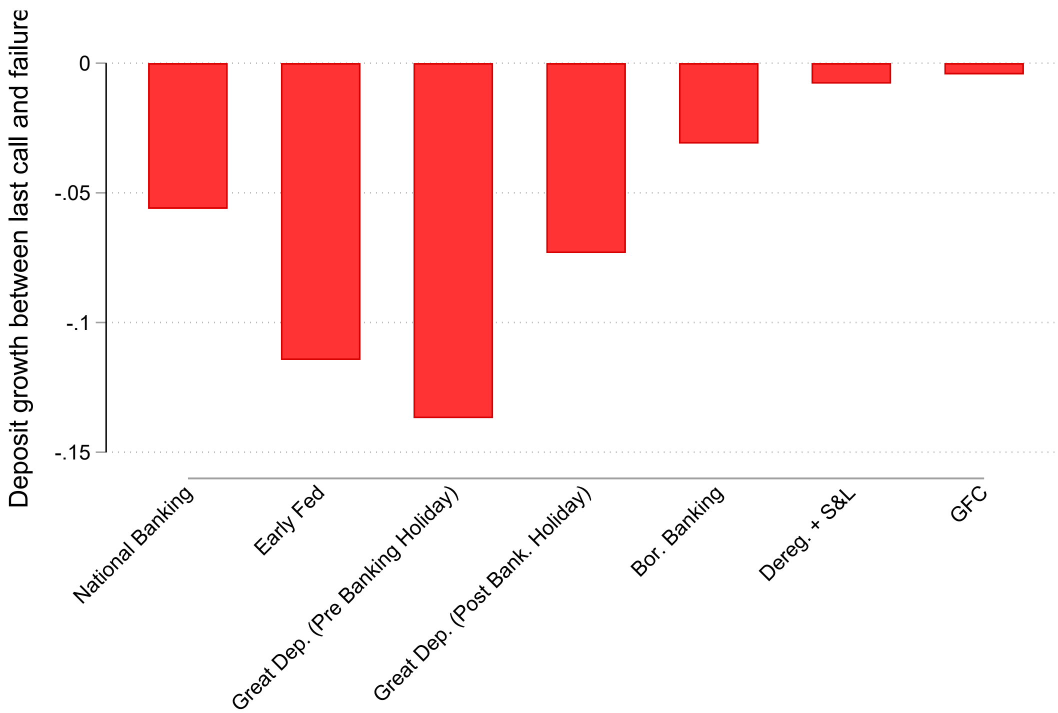
report before failure and deposits reported at the time of failure.[15] Deposit outflows were most pronounced during the National Banking Era and during the Great Depression, especially prior to the bank holiday in March 1933. For example, for banks that failed during the Great Depression before the banking holiday, deposits declined by 13% between the last call and failure. Outflows are much more modest after the introduction of deposit insurance.

This evidence has two implications. First, deposit insurance appears to play an

[15]For the historical sample, deposits at the time failure are the deposits recorded at suspension by the OCC. For the modern sample, deposits at failure are based on deposits in the last financial statement from before failure reported to the FDIC. Typically, this last financial statement will be reflect more recent information than the last publicly available call report but it may not necessarily reflect all outflows before failure. Figure A.8 shows the same figure for the change 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, as we also discuss below in more detail.

important role in reducing outflows before failure, as intended. Second, it invites the possibility some failures in the pre-FDIC era might be driven by depositor behavior. In particular, it allows for the possibility that bank failures were caused by the withdrawal of deposits which in turn may have rendered a bank illiquid first and insolvent second. We discuss the plausibility of this view next by studying the classification of failure causes by the OCC next.

Figure 8: ***Deposit Growth Between Last Call Report and Failure Date by Era***



Notes: This figure reports the percent change between nominal deposits in the last call report before failure and the deposits reported in failure. Before 1935, 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 1935, we use deposits as reported in the FDIC's list of failing banks.

4.5 Post-Mortem: Causes of Failures

Fact 5. From 1863 through 1931, the majority of failures were classified by the OCC as being related to losses, fraud, and external shocks. Despite popular narratives, runs and panics are much less commonly cited as a cause of failure.

Before the introduction of deposit insurance, failing banks experienced large resource outflows. Is failure explained by the run itself? Or are the resource outflows merely a consequence of banks experiencing a deterioration of fundamentals?

One way to make progress on these questions is to consider contemporary accounts of the causes of failure. For each national bank failure occurring between 1863 and 1931, the Annual Report of the OCC provides assessment of the "cause of failure" identified by the bank examiner.[16] Appendix Table B.2 documents how we classify the detailed causes of failure into broad categories: excessive lending, losses, fraud, governance issues, run, external factors, and other factors. The OCC stopped classifying the cause of failure during Great Depression. While it is possible that the OCC classification contains errors or biases, it nevertheless provides insight into what contemporary examiners on the ground saw as the main cause of failure for a bank.

Figure 9 summarizes the distribution of the causes of failure for failures occurring between 1863 and the late 1920s. Fraud and losses are the most common categories. This is followed by external shocks, a category that includes "deflation," "crop loss," and even "robbery and burning of bank." Other common causes are governance issues and excessive lending, which refers to a bank with excessive exposure to one counterparty. On the other hand, failures caused by runs are much less common, accounting just a little more than 1% of all failures. Runs 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.[17]

Altogether, while depositor outflows were substantial in the years and especially

[16] Note that we do not have the cause of failure for the large wave of bank failures that occurred in the Great Depression. Richardson (2007) analyzes the causes of failure during the 1929-1933 period from a different source, the Federal Reserve Board of Governors Division of Bank Operations. He finds that both poor asset quality and illiquidity from withdrawals were both important causes of failure in the Great Depression. Therefore, during the Great Depression, liquidity-driven failures may have been more important than in the pre-Great Depression sample.

[17] 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 also finds that asset losses and fraud were the predominant causes of failure. Even in banking panic years, the OCC only identified one failure due to a bank run.

final months before failure in the pre-FDIC era, the cause of failure according to bank examiners was usually due to a deterioration of fundamental factors, which is also in line with our evidence that failing banks see a disproportional increase in non-performing loans. Failures where the main cause was liquidity pressures or a run are much less common.

Systematic classification of the cause of bank failures by the OCC is not available for the period after 1931. However, Richardson (2007) shows that for the period 1929 through 1933, failures of Federal Reserve member banks were also commonly classified as being due to assets losses. Further, our evidence 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 capital." Poor asset quality was most often caused by poor management decisions and practices, such as imprudent lending practices, excessive loan growth, and fraud.[18] The report also notes that external economic shocks played a role in bringing down banks. However, it emphasized the central role of management practices, arguing that economic decline alone was rarely responsible for driving banks to failure.

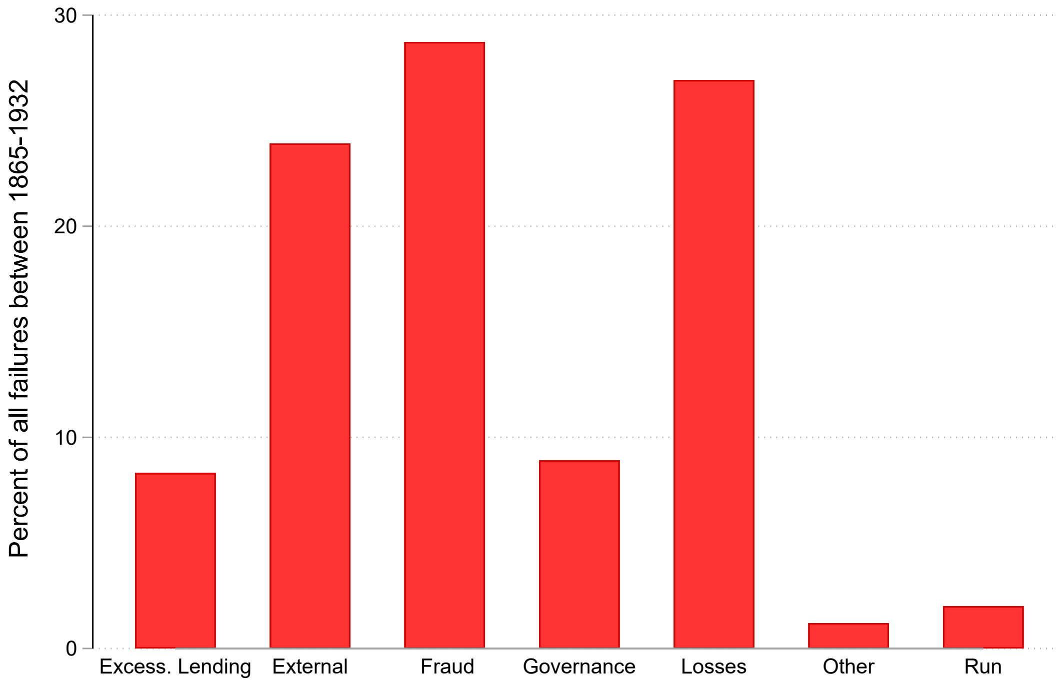
4.6 Asset Recovery Rates and Depositor Loss Rates

Fact 6. Before 1935, the average recovery rate on assets after bank failures was less than 50% and loss rated for depositors around 46%.

Table 2 provides statistics of assets failing bank held at suspension and the ultimate

[18] 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.*"

Figure 9: ***Causes of Failure as Classified by the OCC: 1863-1931***



Notes: Causes of failure are as classified by the OCC in the annual reports table of national banks in charge of receivers. We categorize the broader list of failure reasons as described in Appendix B.2. Figure B.5 shows that the classification of the causes of bank failures by the OCC became increasingly uncommon in the late 1920s and stopped by 1931.

recovery from assets for the period from 1863-1935. The columns "Assets at suspension" are based on estimates about the share of "good," "doubtful," and "worthless" assets at the time of failure. These estimates are provided by the OCC bank examiner at the time of failure. Worthless assets range from 12% to 23% of total assets, depending on the era considered. Doubtful assets are another 36-50%. Therefore, bank examiners tended to judge the assets of failing banks to be highly troubled.

The ultimate recovery from assets represents the value that the receiver was ultimately able to obtain from both assets available at suspension and received after suspension. Recovery rates from assets were very low in the pre-1935 sample, ranging from 41% to 49%. Figure A.9 in the Appendix shows recovery rates across time from 1863 through 1935. Recovery rates fluctuate between 40% and 60% and are lowest during severe downturns, such as after the Panic of 1873, the Panic of 1893, and the Great Depression. At the same time, failure also incurred legal expenses and expenses for the receiver's salary. These ranged from 4-6% of assets at failure. This is larger than the estimated direct costs of financial distress for non-financial firms.[19]

The fact that bank assets lose value in default does not necessarily allow to draw definite conclusions about the ultimate cause of failure. After all, bank assets may carry lower valuations in bank failure than outside of bank failure. This, in turn, allows for the possibility that runs that forced banks to close could have also reduced the value of the assets held. Asset values and recovery rates may in principle drop *because* the bank closed. Thus, it is not straightforward to conclude that the low recovery rates necessarily reflect realized losses from poor fundamentals.[20] Nonetheless, we believe it is striking that examiners already identified nearly 70% of assets as having doubtful or worthless value right at the time of suspension. 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 at least in part a key driver in triggering ultimate failure.[21] Consistent with this, Appendix Table A.4 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 76 cents, 32 cents, and 25 cents, respectively.

The low recovery rates on assets in the pre-1935 sample meant that loss rates for depositors were substantial. Table 3 presents estimates on the loss rates for uninsured depositors for bank failures for both the pre- and post-FDIC samples. Loss rates for uninsured depositors are significantly higher before the founding of the FDIC. Before the

[19]Weiss (1990) estimates that the direct costs of financial distress (legal and other professional and administrative fees associated with the bankruptcy filling) amount to 3.1% of the book value of debt plus the market value of equity.

[20]Observe that the value of assets held at suspension is cannot be reduced through a potential fire sale preceding failure. Rather they reflect the ultimate value after orderly liquidation during the bankruptcy proceedings which allowed to hold the assets to maturity.

[21]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. Our evidence is broadly consistent with James (1991), although we find that the recovery rates were lower in the historical sample.

Table 2: ***Losses in Failures by Share of Total Assets Available in Receivership.***

Era	No. of failures	Assets at suspension			Received after suspension	Ultimate recovery from assets	Legal expenses & Receiver salary & Other expenses
		Good	Doubtful	Worthless			
National Banking Era	530	0.32	0.36	0.23	0.12	0.46	0.07
Early Federal Reserve	637	0.31	0.36	0.22	0.12	0.49	0.07
Great Depression	1690	0.33	0.50	0.12	0.08	0.40	0.05
All	2857	0.32	0.44	0.17	0.09	0.43	0.06

Notes: Data collected from the OCC's annual report to congress; tables on "National banks in charge of receivers," (various years). All values are reported as a share of total assets available in failure which is the sum of "assets at suspension" and "received after suspension". The ultimate receiver is the total collected funds in receivership normalized by total assets represents the share of assets that the receiver was ultimately able to recover. Note that the receiver also collected funds from shareholder due to double-liability which increased the overall amount of available funds to distribute to debt holders. The final payout to debt holders is calculated as the total collected funds from both shareholders and assets net of legal expenses, salary of the receiver and other expenses. Eras are defined as in Table 1.

FDIC, 77% of failures involved losses for depositors, and the average unconditional loss rate was 46%. In the post-FDIC period, only 20% of failures involved losses for uninsured depositors, and the average unconditional loss rate was 6%.

5 Predicting Bank Failures

Failing banks follow systematic patterns in terms of asset growth, funding, and losses in the decade before failure. In this section, we study the extent to which these systematic patterns allow for the prediction of bank failures. The purpose is twofold. First, quantifying the predictability of bank failures based on systematic patterns in failing banks is of practical interest. Second, the degree of predictability of bank failures allows us to make inferences about the causes of failures.

On the one hand, if failures are due to non-fundamental panic runs, then failures should not be predictable based on bank fundamentals. Under this view, bank failures and the widespread bank failures that constitute banking crises are "bolts from the blue," as noted by Greenwood et al. (2022). Self-fulfilling runs and sunspot equilibria are, by

Table 3: ***Loss Rates for Uninsured Depositors in Bank Failures: Pre-FDIC versus Post-FDIC.***

Era	Number of failures	Failures with losses to depositors	Conditional loss rate	Unconditional loss rate
Panel A: Pre-FDIC				
National Banking Era	530	0.64	0.39	0.27
Early Federal Reserve	637	0.84	0.53	0.49
Great Depression	1690	0.79	0.54	0.52
All	2857	0.46	0.52	0.46
Panel B: Post-FDIC				
1992-2008	302	0.43	0.24	0.10
2008-2022	536	0.06	0.43	0.03
All	838	0.2	0.28	0.06

Notes: The recovery rates reported in panel (A) are from the OCC's tables on national banks placed in receivership. The final recovery rate for depositors does not take interest payments into account. The data in panel (B) are as reported in FDIC (2023).

definition, orthogonal to bank fundamentals.

On the other hand, if failures are driven by deteriorating fundamentals, or deteriorating fundamentals that cause creditors to coordinate on a run (see, e.g., Allen and Gale, 1998; Goldstein and Pauzner, 2005), then failures could be either unpredictable or predictable. Fundamental failures are not necessarily predictable if they result from the realization of an unexpectedly large shock. However, fundamental failures are predictable if risk builds up gradually as a consequence of excessive lending, low capitalization, and a fragile funding structure. These vulnerabilities, in turn, can be related to past lending behavior and deteriorating fundamentals.

To quantify the extent to which bank failures are predictable, we estimate simple predictive regression models of the following form:

$$\begin{aligned} \text{Failure}_{b,t+s} = \alpha &+ \beta_1 \times \text{Solvency}_{bt} + \beta_2 \times \text{Funding}_{bt} \\ &+ \beta_3 \times \text{Solvency}_{bt} \times \text{Funding}_{bt} \\ &+ \beta_4 \times \text{Bank Growth}_{bt} + \beta_5 \times \text{Aggregate Conditions}_t + \epsilon_{b,t+s}, \end{aligned} \tag{2}$$

where $\text{Failure}_{b,t+s}$ is a dummy that is one if bank b fails in year $t+s$. We are interested in both the sign and magnitude of the coefficients on the independent variables, as well as the ability to predict failure using the explained variation. Due to differences in data availability across samples, we estimate this model on a full bank-level panel separately for the National Banking Era (1863-1904), Early Fed (1914-1928), Great Depression (1929-1935), and modern era (1959-2023).

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 Solvency_{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 Funding_{bt}. These measures are meant to proxy for the "flightiness" of the funding structure, such as the reliance on non-core funding. For example, wholesale funding investors are typically the most risk sensitive investors (see, e.g. Perignon et al., 2018; Blickle et al., 2022).[22] The exact variables we use for Solvency_{bt} and Funding_{bt} will differ across samples due to differences in data availability.

We also consider the interaction between the solvency and funding measures. The combination of low solvency and fragile funding structure could further increase the failure probability, over and above the direct effect of each source of vulnerability. A bank that has weak solvency *and* has more risk-sensitive financing may see a hastier demise, as these creditors raise the cost of financing or withdraw financing more quickly as losses mount.

Third, Bank Growth_{bt} is a set of variables that capture bank-specific growth. We use five quintiles of the three-year change in log bank assets. This allows us to capture the potentially non-linear relation between past growth and failure documented in Figure 3. Fourth, for $\text{Aggregate Conditions}_t$, we include aggregate real GDP growth over the same

[22] Persistent reliance on expensive forms of funding such as wholesale funding and time deposits can also contribute to lower solvency by depressing bank profitability, so the measures of funding also indirectly effect solvency.

three-year period. This variable captures the idea that bank failures may be more likely following the increase in the likelihood of a business cycle downturn, as argued by Gorton (1988) and Calomiris and Gorton (1991). These latter two measures are available in the same form throughout the entire 1863-2023 sample.

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.[23]

The grouping of variables into categories based on solvency, funding, growth, and aggregate conditions provides insights into which vulnerabilities are most strongly associated with failure. However, we stress that these variables are endogenous and interrelated. For example, a bank could have a more flighty 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. Thus, we cannot make direct inferences about whether failures were caused by fundamentals alone, or by panic-based runs due to deteriorating fundamentals, based on which measures best predict failure.

5.1 Predicting bank failures: 1863-1904

For the historical period covering the National Banking Era (1863-1904)[24], we measure solvency using two variables. First, we use Other Real Estate Owned as a share of total

[23]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).

[24]We end in 1904 and not in 1913 due to changes in the line items reported in 1905.

loans to proxy for non-performing loans (NPL/Loans). Second, we use an indicator variable for times when a bank is restricted form paying out dividends. National banks were not allowed to distribute dividends if undivided profits fell below 1% of equity. This occurrence signalled previous losses that resulted in a low surplus.[25] In addition, to proxy for funding vulnerabilities, we use the share of wholesale funding in total assets. As shown in Figure 5 and Figure 6 above, all three measures mentioned here are elevated in failing banks.

Table 4 presents the estimates of equation (2) for the 1863-1904 sample. We report results for exercises predicting failure in the next year. Columns 1 and 2 show that measures of solvency and funding are both strongly associated with subsequent failure. Banks with higher non-performing loans, restricted dividend payouts, and a greater reliance on wholesale funding are significantly more likely to fail. Therefore, banks with deteriorating solvency and a vulnerable funding structure are most likely to fail. Interestingly, the interaction between proxies for deteriorating solvency and vulnerable funding is highly significant (column 3).

Measures of bank growth are also significantly associated with failure. In the short-term, banks with low asset growth have the highest probability of failure. For example, being in the lowest quintile of the asset growth distribution implies a 0.70 percentage point higher probability of failure next year, relative to banks in the middle quintile (column 4). Aggregate conditions also matter. Low aggregate GDP growth over the past three years is associated with a higher probability of failure.

At the bottom of Table 4, we report the AUC for each predictive regression; Figure A.12 in the Appendix also presents a visualization of the ROC curve across models and horizons. The predictive content of fundamental variables is high. On their own, the measures of solvency, funding, and bank growth have an AUC of 78%, 81%, and 73%,

[25] We have also used Equity/Assets as the measure of solvency. As described above, however, bank equity may not adjust quickly to realized losses in this period due to a lack of accounting standards, so it is a less powerful predictor of failure in this sample.

Table 4: ***Predicting Bank Failures: 1863-1904***.

Dependent variable	Fail next year				
	(1)	(2)	(3)	(4)	(5)
Solvency:					
- NPL/Loans	9.94***		2.98**		2.58*
	(1.67)		(1.35)		(1.34)
- Dividend Payout Restricted	2.42***		2.12***		2.07***
	(0.39)		(0.38)		(0.38)
Funding:					
- Wholesale Funding/Assets		19.24***	10.39***		10.25***
		(2.11)	(2.24)		(2.23)
Solvency $\times$ ***Funding:***					
- NPL/Loans $\times$ WF/Assets			361.90***		357.45***
			(87.15)		(87.20)
Bank Growth:					
- Q1 of Growth from t-3 to t				0.70***	0.48***
				(0.10)	(0.09)
- Q2 of Growth from t-3 to t				0.24***	0.22***
				(0.07)	(0.07)
- Q4 of Growth from t-3 to t				0.15**	0.19**
				(0.07)	(0.08)
- Q5 of Growth from t-3 to t				0.02	0.13
				(0.08)	(0.08)
Aggregate Conditions:					
- GDP Growth from t-3 to t				-1.47***	-0.69**
				(0.29)	(0.27)
N	49799	49799	49799	53877	49761
No of Banks	4525	4525	4525	4902	4522
Mean of dep. var.	.47	.47	.47	.46	.47
AUC	0.781	0.814	0.854	0.727	0.857

Notes: This table presents estimates of (2) with failure in $t+1$ as the dependent variable for the 1863-1904 sample. We also estimate the same specification using failure in $t+5$ as dependent variable, see Table A.5 in the Appendix. We estimate the model using OLS; Table A.9 reports results using Logit. In addition to the reported predictor variables, we also include the log of a bank's age. Standard errors in parentheses are clustered at the bank level; *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

respectively. Interestingly, adding the interaction between solvency and funding boosts the AUC even further to 85% (column 3). The full specification in column 5 has a similar AUC. Overall, bank failures are highly predictable based on deteriorating solvency and a reliance on non-core funding. This cuts against the view that failures in in the National Banking Era, before the Federal Reserve and deposit insurance, were driven by non-fundamental sunspot runs, consistent with the evidence on the OCC's assessed cause of failure.

5.2 Predicting bank failures: 1914-1935

Table 5 presents the results from predicting bank failures in the 1914-1935 period. This period includes the elevated failures during the 1920s and the surge in failures during the Great Depression. Because of changes in which balance sheet items are reported, we divide this sample into two sub-periods: Early Fed (1914-1928) and the Great Depression (1929-1935).

Columns 1-5 in Table 5 present the results from the Early Fed period (1914-1928). For this sample, as measures of solvency, we use equity-to-assets, surplus-to-equity, and loans-to-assets. For funding, we use time deposits as a share of total deposits, as time deposits represent a more expensive and risk-sensitive source of funding.

Table 5 shows that measures of deteriorating solvency and vulnerable funding structure both predict a highest risk of failure (columns 1 and 2). Here, the predictive power of the solvency measures is considerably higher, with an AUC of 75% compared to 63%. The interaction between solvency and funding adds a significant additional boost to the prediction, raising the AUC to 84% (column 3). Table 5 also reveals that banks with the lowest asset growth are significantly more likely to fail next year (column 4). Macroeconomic downturns are also associated with a higher rate of failures (column 4). In the 1914-1928 sample, the complete model with all variables has an impressive AUC of 88.5%.

Table 5: ***Predicting Bank Failures: 1914-1935*.**

Dependent variable	Fail next year									
Sample	1914-1928					1929-1935				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Solvency:										
- Equity/Assets	-2.48***		-1.28***		-3.43***	-6.00***		-5.98***		-8.97***
	(0.40)		(0.48)		(0.52)	(1.23)		(1.19)		(1.26)
- Surplus/Equity	-3.17***		-2.24***		-1.72***	-6.19***		-2.34***		-1.31***
	(0.24)		(0.36)		(0.35)	(0.48)		(0.43)		(0.42)
- Div. Payout Restricted						2.28***		1.34***		1.14**
						(0.48)		(0.47)		(0.47)
- Loans/Assets	0.97*		0.95*		0.90*	9.66***		5.19***		4.96***
	(0.56)		(0.57)		(0.54)	(0.71)		(0.60)		(0.59)
Funding:										
- Time Deposits/Deposits		0.66***	2.38***		2.18***					
		(0.10)	(0.49)		(0.48)					
- Wholesale Funding/Assets							64.64***	104.64***		102.58***
							(3.83)	(8.80)		(8.82)
Solvency × Funding:										
- Surplus/Equity × Time Dep./Dep.			-3.51***		-3.68***					
			(0.89)		(0.88)					
- Surplus/Eq. × WF/Assets								-137.48***		-134.25***
								(19.13)		(19.16)
Bank Growth:										
- Q1 of Growth from t-3 to t				1.22***	1.06***				3.40***	2.10***
				(0.09)	(0.12)				(0.31)	(0.30)
- Q2 of Growth from t-3 to t				0.14**	0.14*				1.00***	0.63**
				(0.06)	(0.08)				(0.26)	(0.24)
- Q4 of Growth from t-3 to t				-0.13***	-0.07				-0.90***	-0.22
				(0.05)	(0.07)				(0.22)	(0.20)
- Q5 of Growth from t-3 to t				0.00	-0.17**				-0.61***	-0.29
				(0.05)	(0.07)				(0.22)	(0.21)
Aggregate Conditions:										
- GDP Growth from t-3 to t				-0.90***	-1.13***				-4.91***	-0.94***
				(0.05)	(0.08)				(0.36)	(0.35)
N	69156	63137	62328	109163	62214	31134	31353	31078	39356	30979
No of Banks	9151	9066	9055	9429	9053	7369	7369	7363	7504	7359
Mean of dep. var.	.53	.56	.55	.57	.55	2.2	2.2	2.2	2.9	2.2
AUC	0.749	0.627	0.835	0.757	0.885	0.751	0.773	0.820	0.770	0.832

Notes: This table presents OLS estimates of (2) with failure in $t+1$ as the dependent variable for the 1914-1935 sample. Table A.6 shows results when using failure in $t+5$ as the dependent variable. Table A.10 shows results when using Logit as opposed to OLS.Columns (1) through (5) are estimated with using data from 1914-1928. In columns (6) through (10) we use data from 1929 through 1935. We split the sample due to changes in the reported line items in 1929.Standard errors in parentheses are clustered at the bank level; *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Columns 6-10 in Table 5 report the results from the Great Depression period (1929-1935). In this period, we have information on whether dividend payouts are restricted due to low surplus, so we include this in the set of solvency measures. For the funding variables, the data no longer distinguishes between demand and time deposits. However, it does report wholesale funding, so we use wholesale funding as a share of total assets as the measure of funding vulnerability.

In the Great Depression, failure is predictable based on deteriorating solvency and a reliance on more fragile wholesale funding (Table 5 columns 6 and 7). The AUC for the solvency and funding variables are similar, at 75% and 77%, respectively. The interaction between low solvency and fragile funding is, once again, highly statistically significant and adds considerable predictive content, raising the AUC to 82%. Furthermore, banks with low asset growth and time periods with lower GDP growth both predict a higher rate of failure. Column 10 presents estimates of the full model that combines measures of solvency, funding, bank growth, and aggregate conditions. This model yields an AUC of 83%. The high predictive content of fundamental measures echoes the results in Calomiris and Mason (1997), who also find that fundamentals explain bank failures well during the Great Depression.

5.3 Predicting bank failures: 1959-2023

The predictability of bank failures is even stronger in the modern era. Table 6 presents the results from estimating equation (2) for the 1959-2023 sample. For this sample, our main measure of solvency is net income-to-assets.[26] To measure funding fragility, we use time deposits as a share of total deposits which are commonly more sensitive to bank riskiness than demand deposits (see Martin et al., 2022).[27]

[26]Other measures such as equity/assets and non-performing loans perform equally well. See, e.g., Table A.8 in the Appendix.

[27]Alternatively, we can measure funding fragility using the share of wholesale funding over assets or the share of uninsured deposits over assets.

Column 1 in Table 6 shows that net income to assets, our measure of solvency, is a strong predictor of failure. The predictive content of each of this variable is extremely high, with an AUC value above 94%. Funding structure also predicts failure. Banks with a highest share of time deposits are considerably more likely to fail in the following year. The AUC for this measure is somewhat lower, at 81%. As we saw in the historical sample, the interaction between solvency and funding fragility predicts a higher rate of failure. However, deteriorating solvency alone has essentially the same predictive content in terms of the AUC, suggesting that funding vulnerabilities are less central to failure after the introduction of deposit insurance compared to the historical sample.

The proxies for Bank Growth$_{bt}$ also predict failure in the short-term. Banks in the lowest quintile of the growth distribution are significantly more likely to fail in the next year. Interestingly, the relation between failure and bank asset growth is U-shaped, with a slight increase in failure probability for banks with the fastest growth. Low aggregate GDP growth also predicts failure in the short term. Qualitatively, these patterns are similar to the historical sample.

There are likely to be several reasons for the stronger predictive performance in the modern sample. First, the quality of the accounting data is higher in the modern sample. For example, the modern data has information on income statements, and losses are also reflected sooner through explicit accounting for NPLs and loan-loss provisioning. Second, in the historical sample, national banks with unit-branches were likely less diversified, implying that idiosyncratic shocks accounted for more failures. This makes these failures harder to predict.

5.4 Predicting Failure at Longer Horizons

We find that bank failures are also substantially predictable at longer horizons. Focusing on longer horizons is of interest, as banks and policymakers have more scope to intervene if an elevated likelihood of failure can be detected with sufficient lead time. Figure 10

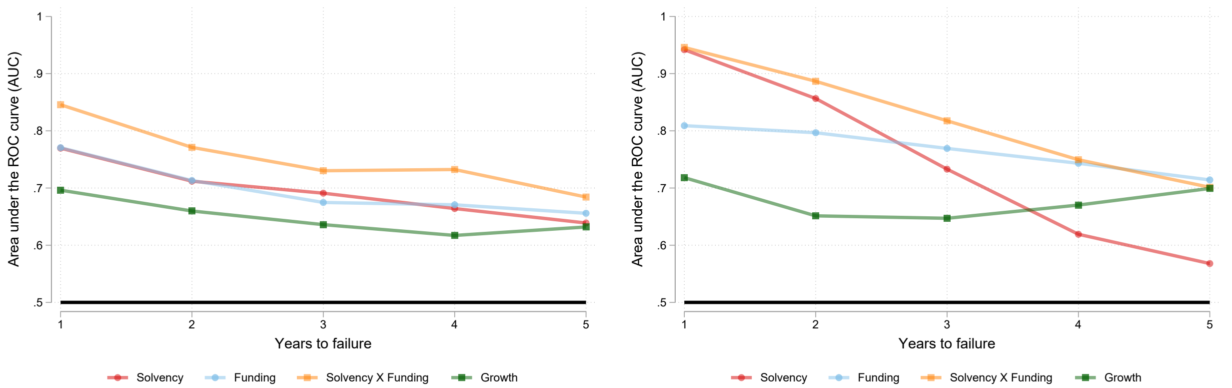
Table 6: ***Predicting Bank Failures: 1959-2023*.**

Dependent variable	Fail next year				
	(1)	(2)	(3)	(4)	(5)
Solvency:					
- Net Income/Assets	-53.86***		11.80***		12.37***
	(2.17)		(1.76)		(1.94)
Funding:					
- Time Deposits/Deposits		2.18***	4.36***		4.40***
		(0.07)	(0.16)		(0.15)
Solvency* $\times$ *Funding:					
- Net Inc./Assets $\times$ Time Dep./Dep.			-355.94***		-358.44***
			(17.39)		(18.24)
Bank Growth:					
- Q1 of Growth from t-3 to t				0.58***	0.08**
				(0.03)	(0.03)
- Q2 of Growth from t-3 to t				0.02	-0.06***
				(0.01)	(0.01)
- Q4 of Growth from t-3 to t				0.03*	0.03**
				(0.01)	(0.01)
- Q5 of Growth from t-3 to t				0.15***	0.02
				(0.02)	(0.02)
Aggregate Conditions:					
- GDP Growth from t-3 to t				-1.11***	-0.05
				(0.08)	(0.12)
N	616298	614994	614928	606404	604984
No of Banks	22102	22108	22099	22085	22073
Mean of dep. var.	.27	.27	.27	.27	.27
Sample	1959-2023	1959-2023	1959-2023	1959-2023	1959-2023
AUC	0.944	0.806	0.950	0.718	0.951

Notes: This table presents OLS estimates of (2) with failure in $t+1$ as the dependent variables for the 1959-2023 sample. Table A.7 in the Appendix shows estimate when using failure in $t+5$ as the dependent variable. We estimate the model using OLS; Table A.13 reports results from a Logit estimation. In addition to the reported predictor variables, we also include the log of a bank's age. Standard errors in parentheses are clustered at the bank level; *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Figure 10: *Area under the curve at different prediction horizons*

(a) *1889-1904* **(b)** *1959-2023*



Notes: Panel (a) shows the AUC for the four models estimates in columns (1) through (4) of Table 4 when varying the time horizon of the LHS variable from $t+1$ up to $t+5$. Panel (b) shows the AUC for the four models estimates in columns (1) through (4) of Table 6 when varying the time horizon of the LHS variable from $t+1$ up to $t+5$.

shows the AUC for across different models and different prediction horizons. Further, Table A.5, Table A.6, and Table A.7 in the Appendix report estimates of equation (2) where the dependent variable is failure in five years for the 1863-1904, 1914-1935, and 1959-2023 samples.

Measures of solvency and funding predict failure in five years with the same sign as in the short-term. However, the magnitudes of the estimates and the predictive content in terms of AUC is substantially lower for these measures. For example, the AUC for solvency in the modern sample falls from 94% to 54% when going from predicting failure in one year to predicting failure in five years (see panel (b) of Figure 10). This is consistent with losses rising in the years before failure and therefore only providing a strong signal close to failure, as we showed in Section 4.3.

The distribution of bank asset growth also predicts failure at longer horizons. However, in contrast to short horizons, at longer horizons the highest probability of failure is for banks that grow *quickly* from $t-3$ to t, consistent with the evidence in Section 4.1.[28] In

[28]This holds for the National Banking Era sample (1863-1904) and the modern sample (1959-2023). However, for the Early Fed and Great Depression samples (1914-1935), banks with the lowest growth are also most likely to fail in five years.

fact, the relative predictive performance of the solvency versus growth measures switches when moving from predicting failure in the short-run to the medium run, especially in the modern sample, see Figure 10. In the modern sample, bank growth and aggregate conditions yield have an AUC of 70% for predicting failure in five years, compared to the AUC of 54% for the solvency measure.

6 Fundamentals and Aggregate Waves of Bank Failures

The failure of individual banks is highly predictable based on past fundamentals. In this section, we ask whether the predictability of bank failures based on fundamentals carries 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).[29]

We find no evidence that fundamentals are less predictive of bank failures during crises. We find that the AUC is generally higher during times of major banking crises, see Table A.14 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 losses for other banks through interdependent

[29] 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 about healthy from unhealthy banks and even banks with strong fundamentals can fail (Dang et al., 2012).

claims (Allen and Gale, 2000; Acemoglu et al., 2015). Crises can also result in fire sales that weaken all banks (Gertler and Kiyotaki, 2015). 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 exercises 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 a predictive model similar to equation (2) using only data from t_0 to t:

$$\text{Failure}_{bt} = X_{bt-1}\beta + \epsilon_{bt},$$

where X_{bt-1} includes, for instance, Solvency_{bt-1}, Funding_{bt-1}, and their interaction. With this model estimated on data up until t, we predict the bank-specific failure rate in year $t+1$: $p_{b,t+1|t}$ using observables X_{bt} and the estimates $\hat{\beta}_t$. At time t, we thus have the pseudo-out-of-sample predicted probability of failure in $t+1$ for each bank b. We have also the fitted values for each bank from t_0 to t: $\{p_{b,j|t}\}_{j=t_0:t}$

We then compute two statistics that summarize the predicted failure distribution. First, we calculate the share of banks with a predicted failure probability above a cutoff value p_t^{cutoff}:

$$BaR_{t+1} = \frac{\sum_{b \in B_t} \mathbf{1}[p_{b,t+1|t} > p_t^{cutoff}]}{N_t},$$

where B_t is the set of all banks in year t and N_t is the number of banks in year t. We set the cutoff value equal to the 90$^{\text{th}}$ percentile of distribution of $\{p_{b,j|t}\}_{j=t_0:t}$. We refer to BaR_t as *Banks-at-Risk*.[30] This measure captures the thickness of the right tail of the predicted failure distribution.[31] Second, we calculate the weighted average predicted

[30]The name is inspired by Adrian et al. (2019) and Adrian et al. (2022), who define the fifth percentile of the conditional distribution of GDP growth as Growth-at-Risk.

[31]In a similar vein of combining information from micro-data with macro forecast variables, Banerjee et al.

failure rate

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

where w_{bt} is the weight on bank b at time t.

Figure 11 plots the time series of $\overline{p}_t$ and BaR_t along with the realized failure rate in percent. We set $t_{training} = 15$ years. We estimate $\overline{p}_t$ and BaR_t separately for the 1863-1935 and 1959-2023 samples due to differences in data availability.[32] We weight banks by the log of assets to assign higher weight to larger banks. Results are similar without weighting.

Panel (a) of Figure 11 presents the results for the historical sample from 1863 to 1935. *Banks-at-Risk* captures the moderate rise in failures in the Panic of 1884. It also forecasts the large rise in failures in the Panics of 1890 and 1893, as well as the sustained period of high failures during the downturn from 1893 to 1896. *Banks-at-Risk* then declines with the fall in failure rates during the economic expansion after 1896. Notably, the *Banks-at-Risk* measure captures the large spike in failures during the Great Depression. Already in 1929, the *Banks-at-Risk* measure attains its highest value to date, and it rises further in 1930-33, with the large wave of bank failures.

Panel (b) of Figure 11 present the results for the modern sample covering 1959-2023. *Banks-at-Risk* forecasts the protracted wave of failures in the 1980s and early 1990s, during the S&L crisis and the 1990-91 recession. This measure actually leads the rise in failures during the S&L crisis, which might be explained by the fact that regulator forbearance delayed some failures that were inevitable (Kane, 1987). *Banks-at-Risk* also forecasts the sharp spike in failures during the 2008 Global Financial Crisis (GFC). For illustration,

(2022) find that micro-level data on borrower-level repayment ability helps predict aggregate non-performing loan and bankruptcy rates.

[32] In particular, we fit two models. The first model is for the expanding sample covering the 1863-1935 period. For this period, we use a model similar to column 3 Table 4, except we exclude NPL/Loans, as these were not reported after 1904, and we instead include the equity-to-assets ratio. Note that there is a gap in the BaR_t and $\overline{p}_t$ measures from 1904-1928, as we do not observe wholesale funding and dividend restrictions during this period. The second model is for the expanding sample covering the 1959-2023 period. For this period, we use the model in based on column 5 in Table 6.

Figure A.15 in the Appendix shows the distribution of predicted failure shifts substantially to the right between 2004, several years before the GFC, and 2008, at the onset of the GFC.

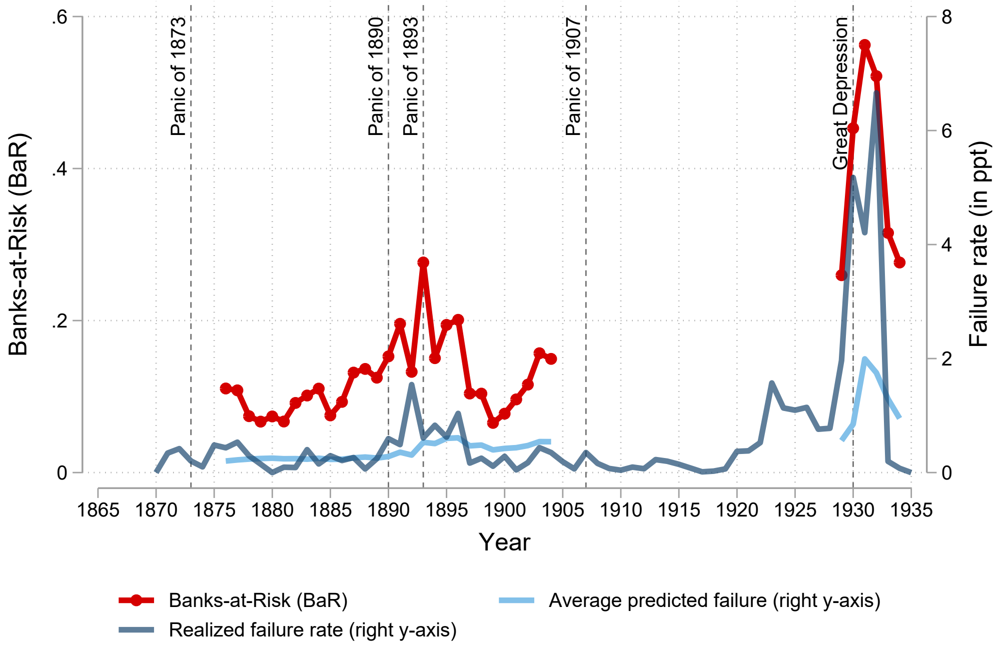
Table 7 presents regressions of the actual bank failure rate on Banks-at-Risk, BaR_t, and the average predicted failure rate, $\overline{p}_t$. Both variables predict failure, but the predictive content of Banks-at-Risk is substantially higher. In the modern sample, the R^2 of the realized failure rate on the predicted failure rate is 90%; in the historical data it is 75%. This indicates that the thickness of the right tail of the failure distribution is the better predictor of waves of failure.

This strong performance of the *Banks-at-Risk* measure in predicting the waves of failure is consistent with the high predictive performance of fundamentals. Moreover, it illustrates that deteriorating fundamentals matter not only for individual banks failures. It also plays an important role in explaining bank failures during the major U.S. bank crises, including the Panics of 1890 and 1893, the Great Depression, the S&L crisis, and the 2008 Global Financial Crisis.

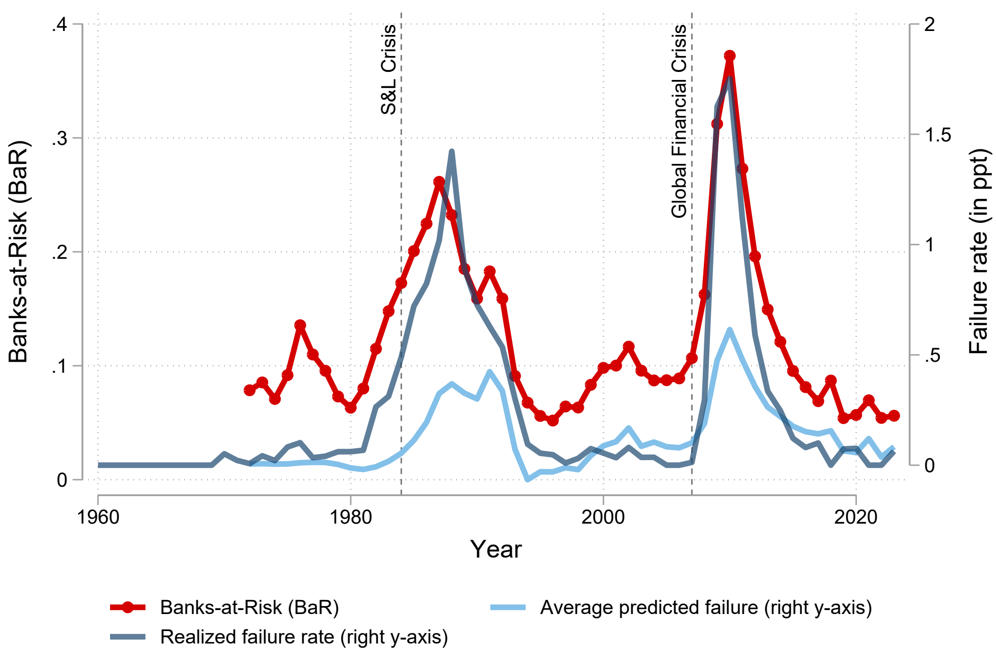
At the same, the average predicted failure rate, $\overline{p}_t$ does not capture the extent of spikes in failures during major crises. Our simple model underpredicts the number of banks that failed in all major crises. This suggests that the average threshold for failure may increase during crises, leading banks that were *ex ante* healthier to fail at a higher rate than they would have during normal times. This is consistent with the importance of amplification mechanisms through contagion channels, which increase systemic fragility during crises. Indeed, the higher predictive performance of *Banks-at-Risk* may be explained by the fact that a thicker right tail of predicted failures is a better proxy for rising systemic fragility than is the average predicted failure rate.

Figure 11: ***Predicting Aggregate Waves of Bank Failures***

(a) *1863-1935*



(b) *1959-2023*



Notes: This figure plots the Banks-at-Risk, BaR_t, and average predicted failure rate, $\overline{p}_t$ measures against the realized failure rate. Both BaR_t and $\overline{p}_t$ are constructed using only information up to year $t-1$, so the prediction is pseudo-out-of-sample. Both measures start 15 years after the start of our data so that we have a sufficiently long training sample. See text for details on the construction of the Banks-at-Risk and average predicted failure measures.

Table 7: ***Banks-at-Risk and Aggregate Bank Failures.***

Dependent variable	Failure Rate					
	(1)	(2)	(3)	(4)	(5)	(6)
Banks-at-Risk (BaR)	10.18***		12.84***	5.77***		5.01***
	(1.08)		(2.56)	(0.33)		(0.40)
Avg. predicted failure rate		2.63***	-0.89		2.37***	0.42*
		(0.43)	(0.77)		(0.34)	(0.24)
N	35	35	35	52	52	52
R^2	.73	.53	.74	.9	.71	.9
Sample	1865-1935	1865-1935	1865-1935	1959-2023	1959-2023	1959-2023

Notes: This table presents time series regression of the annual failure rate in year t on Banks-at-Risk, BaR_t or the average predicted failure rate $\overline{p}_t$. The measures on the right-hand-side are constructed on an expanding sample using only information up to $t-1$. Newey-West standard errors in parentheses with a bandwidth of three years. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

7 Conclusion

This paper studies failing banks using data on 38,630 banks from the United States spanning 1863-2023. We characterize commonalities of failing banks over 160 years. The typical failing bank undergoes a boom and bust in assets in the decade before failure. In the process, it increasingly finances itself with non-core funding. As the bank approaches failure, losses begin to mount, eroding bank solvency. Individual bank failures and systemic banking crises are thus highly predictable based on past fundamentals. Overall, the evidence suggests that the ultimate cause of bank failures is almost always and everywhere related to a deterioration of fundamentals.

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 understand why banks experience predictable fundamental deterioration in asset values that erode bank solvency. What are the frictions that drive decisions which ultimately lead to a deterioration of bank fundamentals? Why do banks sometimes expand rapidly, even though this increases the risk of future failure? 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 most bank failures can be identified supports the use of prompt corrective action measures, such as limiting payouts and the use of non-core funding for poorly capitalized banks.

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Failing Banks
Online Appendix

Sergio Correia, Stephan Luck, and Emil Verner*

December 19, 2023

- Appendix A: Additional Tables and Figures
- Appendix B: Data Appendix

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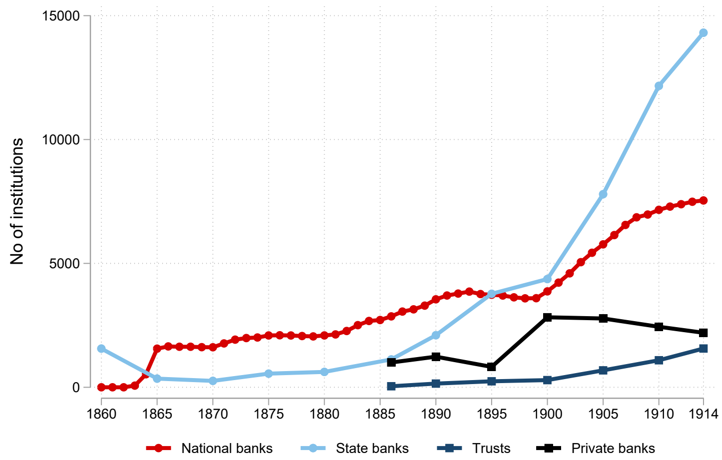
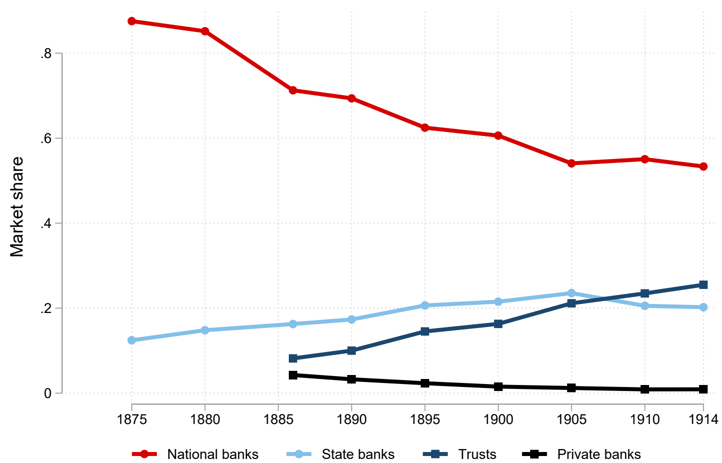
A Appendix Figures and Tables

Figure A.1: ***Number of banks and bank assets by type: 1860-1914.***

(a) *Number of banks*



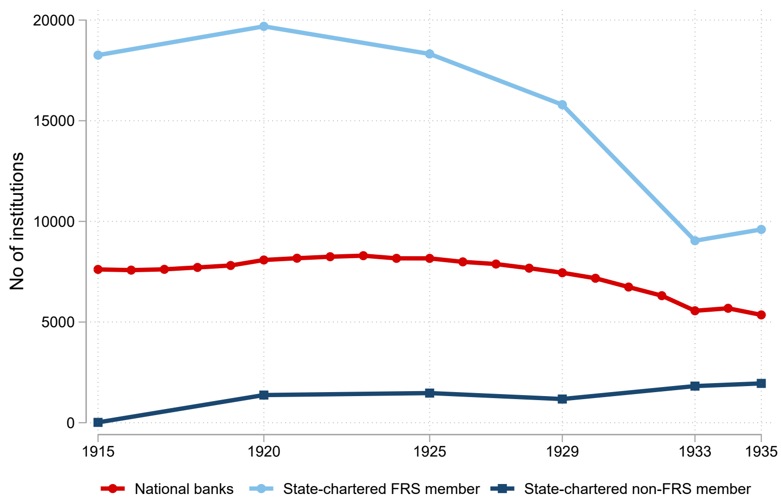
(b) *Market shares based on total assets*



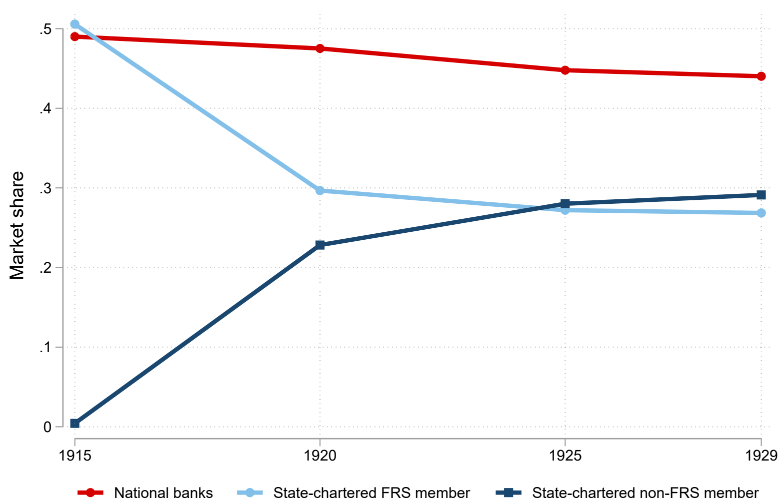
Notes: Data on state banks, trusts, and private bank are taken from White (1983). State bank assets are available from 1875 onwards; assets of trusts and private bank from 1886 onwards.

Figure A.2: ***Number of banks and banks assets by type: 1915-1929.***

(a) *Number of banks*



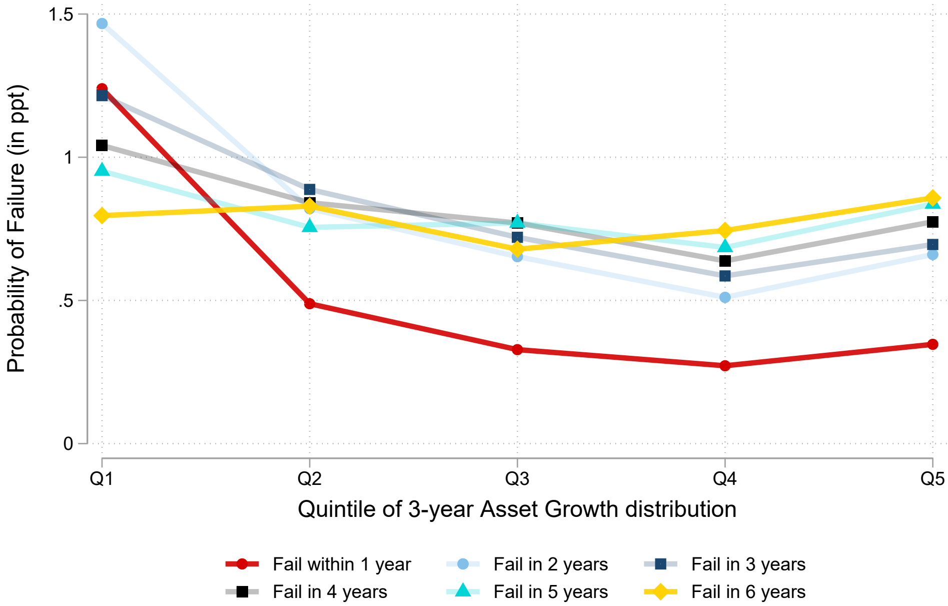
(b) *Market shares based on total deposits*



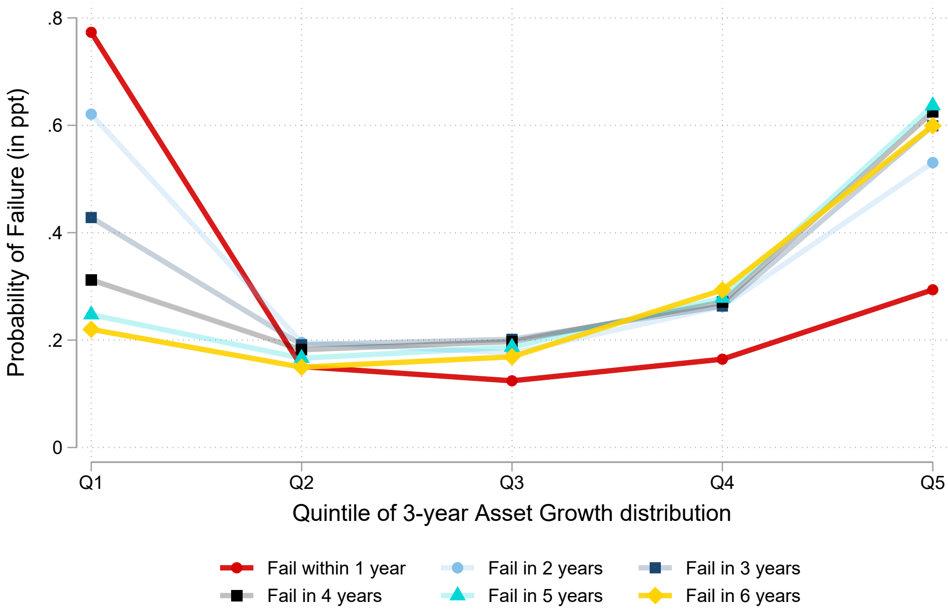
Notes: Data on both state-chartered member and non-member banks are taken from White (1983).

Figure A.3: ***Non-Monotonic Intertemporal Relation between Growth and Failure Probability.***

(a) *Pre-1935*

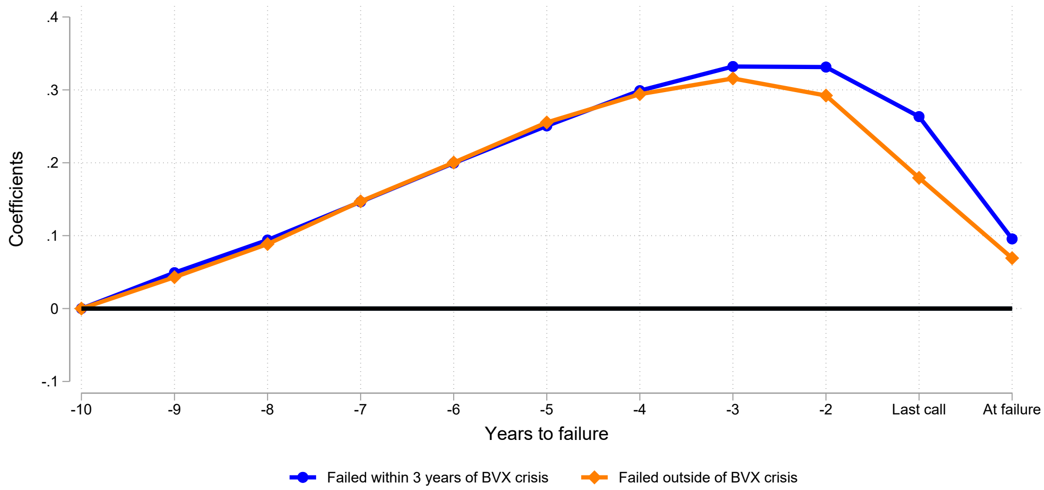


(b) *Post-1935.*



Notes: This figure plots the frequency of failure at the one to six year horizons across quintiles of the three-year asset growth distribution.

Figure A.4: ***Asset Growth for Failures Occurring in Financial Crisis versus Normal Times.***

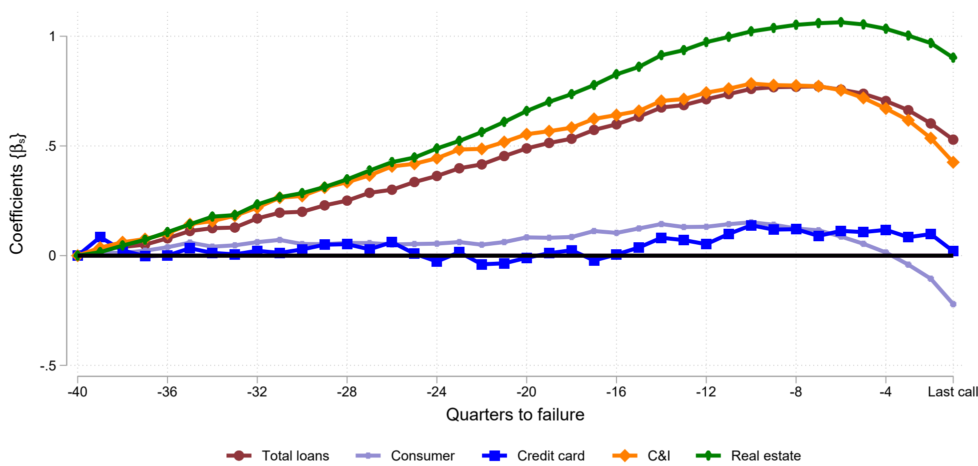


Notes: Both panels shows the sequence of coefficients from a regression of the following form:

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

where y_{bt} is either bank b' assets, deposits, or loans and α_b is a set of bank fixed effects. The sample is restricted to failing banks only and to the ten years before they fail. Financial crises are defined according to Baron et al. (2021)

Figure A.5: ***Asset Growth in Failing Banks is Driven by Real Estate and C&I Lending.***



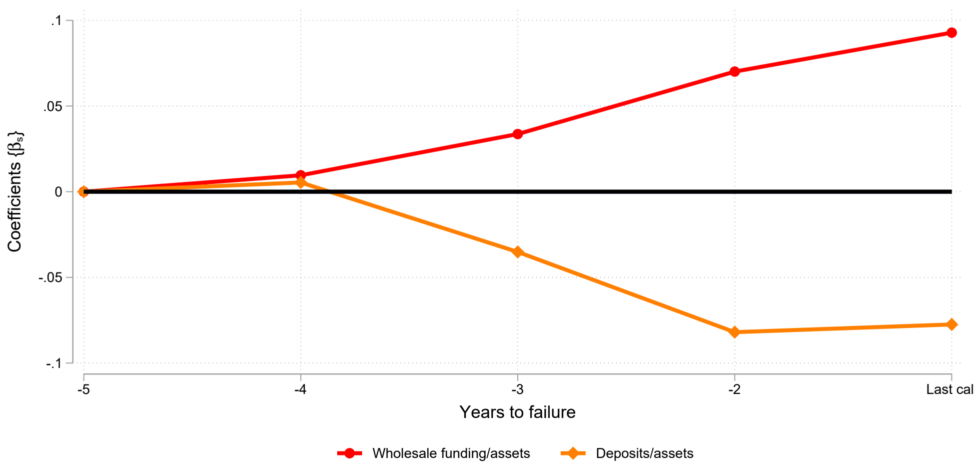
Notes: This figure presents the sequence of coefficients from a regression of the following form

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

where y_{bt} is a type of bank loan. The same is restricted to failing banks and to the ten years before they fail. We also restrict to the post-1959 sample, due to data available on loan types.

Figure A.6: ***Non-Core Funding in Failing Banks, 1929-1935***

(a) *1929-1935: Wholesale Funding and Deposit Funding*



Notes: This figure shows the sequence of coefficients from a regression of the following form:

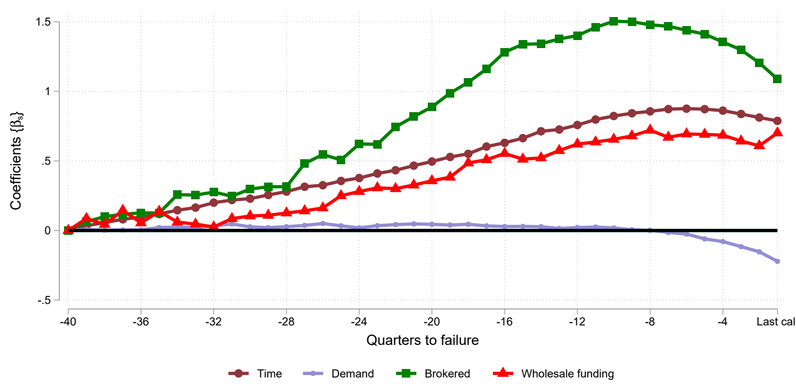
$$y_{b,t} = \alpha_b + \sum_{j=-10, j\neq -10}^{0} \beta_j \times \mathbf{1}_{j=t} + \epsilon_{b,t}$$

where y_{bt} is the ratio indicated in the figure legends and α_b is a set of bank fixed effects. The sample is restricted to failing banks and to the ten years before they fail and the sample indicated in the caption.

Figure A.7: ***Funding of Failing Banks***

(a) *Pre-1935: Deposits and Wholesale Funding*

(b) *Post 1959: Time, Demand, and Brokered Deposits, and Wholesale Funding*

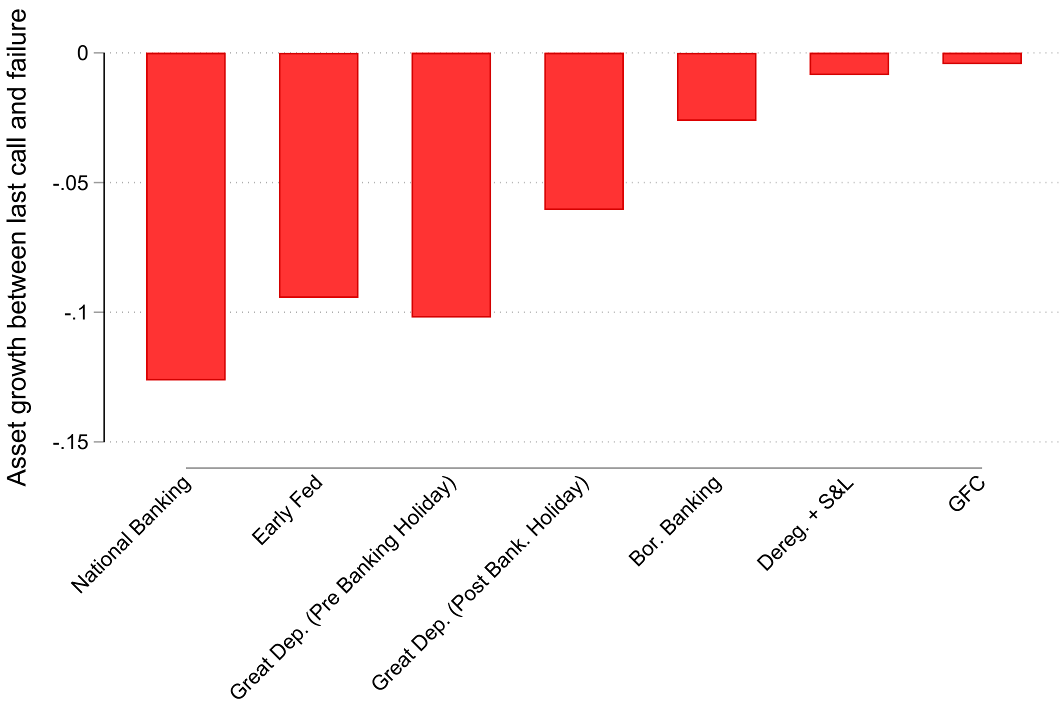


Notes: The figure shows the sequence of coefficients from a regression of the following form:

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

where y_{bt} is the natural logarithm of the line item indicated in the figure legends and α_b is a set of bank fixed effects. The sample is restricted to failing banks and to the ten years before they fail. In panel (a), the sample is restricted to data from 1865 though 1904 and in panel (b) to data from 1959 through 2023.
In panel (a) wholesale funding is defined as the sum of "Bills Payable" and "Rediscounts". In panel (b), 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.

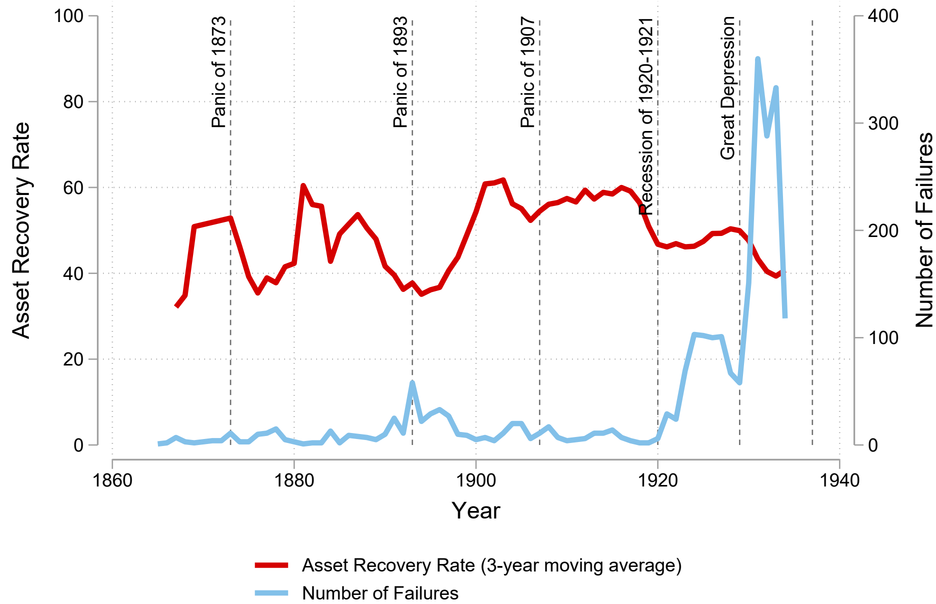
Figure A.8: ***Asset Growth Between Last Call Report and Failure Date by Era***



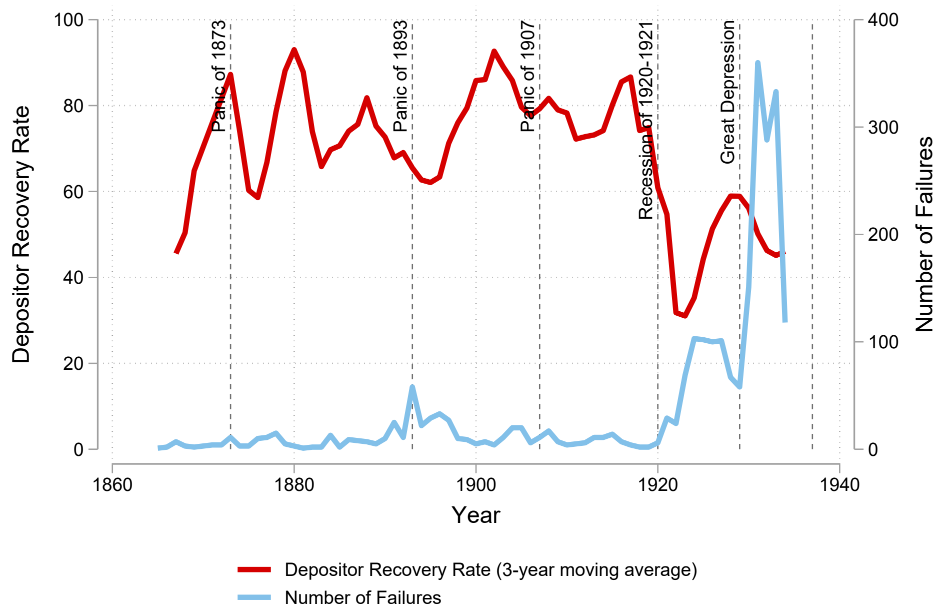
Notes: This figure reports the percent change between nominal asset holdings in the last call report before failure and the asset holdings reported in failure. Before 1935, assets in failure are as reported in the OCC annual reports table on national banks in receivership. After 1935, we use assets as reported in the FDIC's list of failing banks. Note that the assets reported in failure can contain potentially doubtful or worthless assets. Eras are defined as in Table 1.

Figure A.9: ***Recovery Rates***

(a) *Asset Recovery Rate*

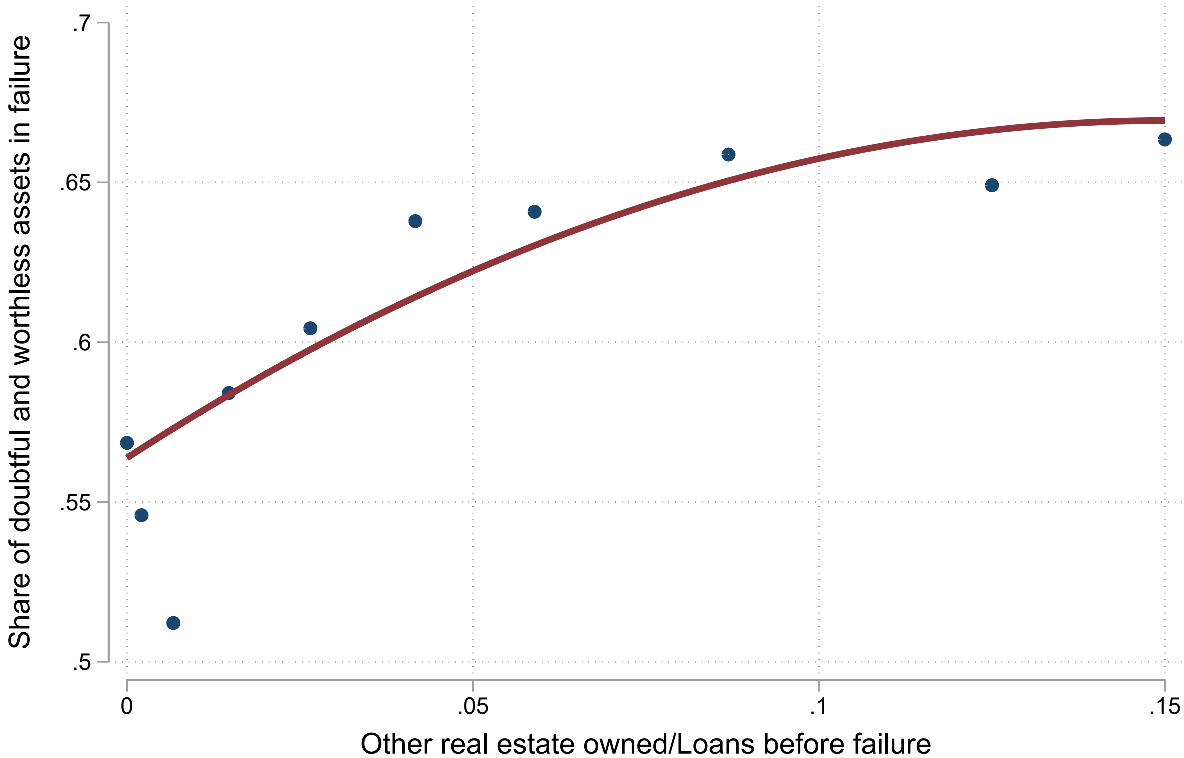


(b) *Depositor Recovery Rate*



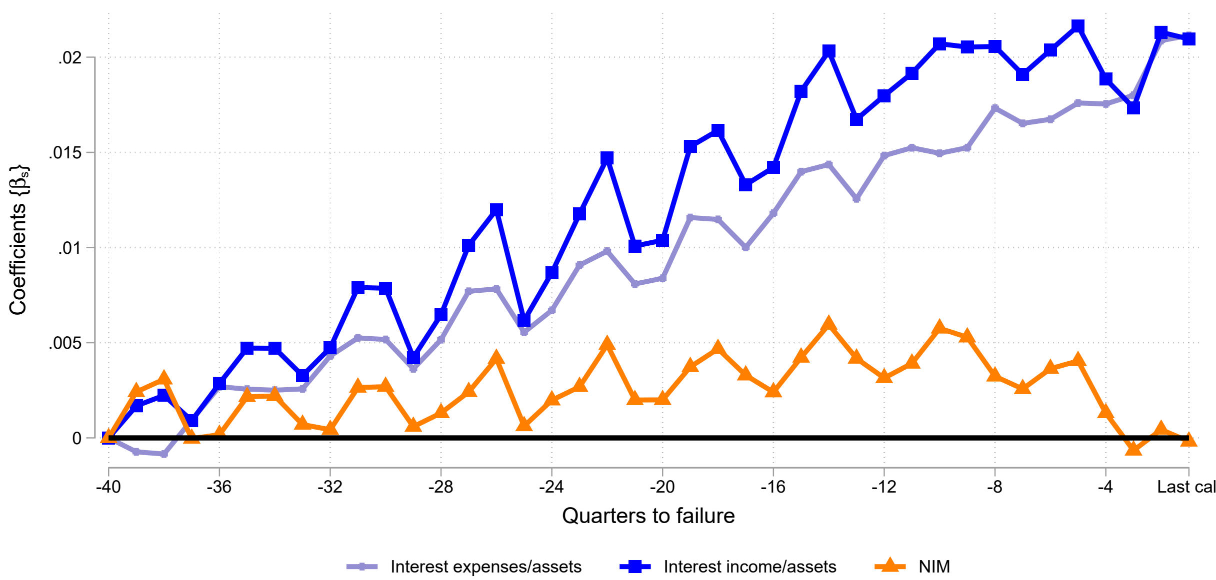
Notes: This figure plots the recovery rate on assets (panel (a)) and deposits (panel (b)) from 1865 through 1935.

Figure A.10: ***Other real estate owned before failure and share of doubtful and worthless assets in failure***



Notes: This figure shows a binned scatter plot correlated the share of Other Real Estate Owned (OREO) a failing banks reports before failure as a share of its total outstanding loans before failure (x-axis) with the share of assets that the OCC classified as "doubtful" or "wortheless" after the bank failed. Data for failing banks from 1867 through 1904.

Figure A.11: ***Interest Income, Expenses and NIM: 1959-2023***

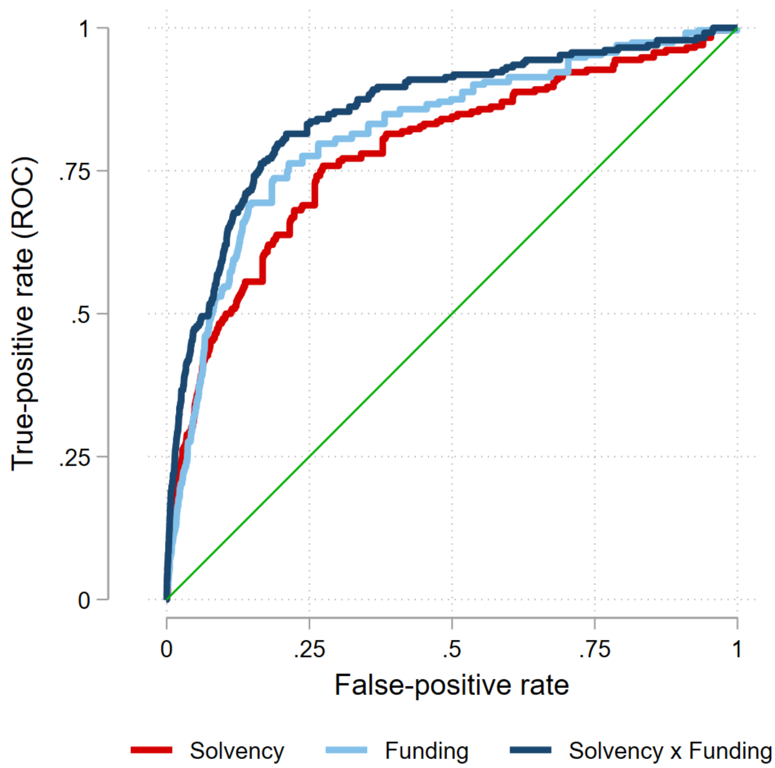


Notes: The figure shows the sequence of coefficients from a regression of the following form:

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

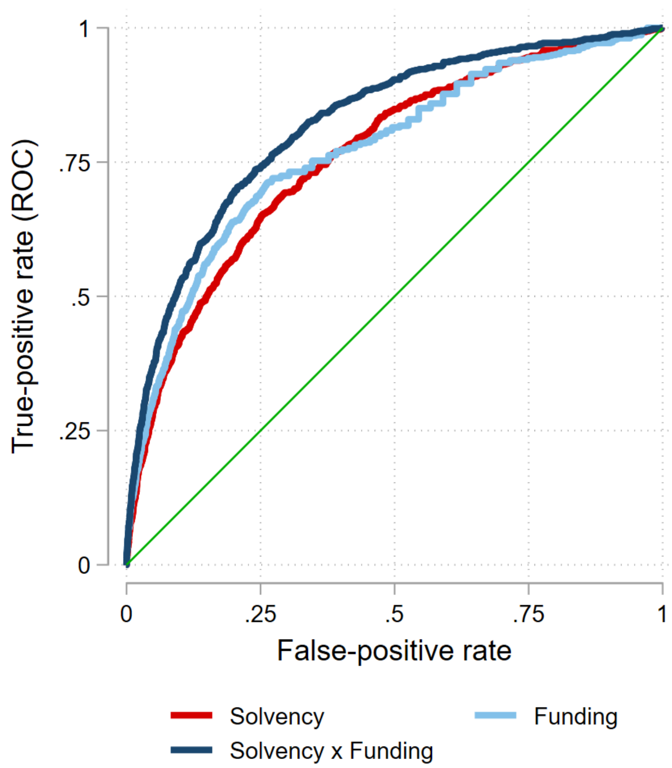
where y_{bt} is the ratio indicated in the figure legends, and α_b is a set of bank fixed effects. The sample is restricted to failing banks and to the ten years before they fail and banks that fail after 1959. The net interest margin (NIM) is defined as the difference of total interest income net of interest expenses normalized by total assets.

Figure A.12: ***ROC Curves: 1889-1904 Sample***



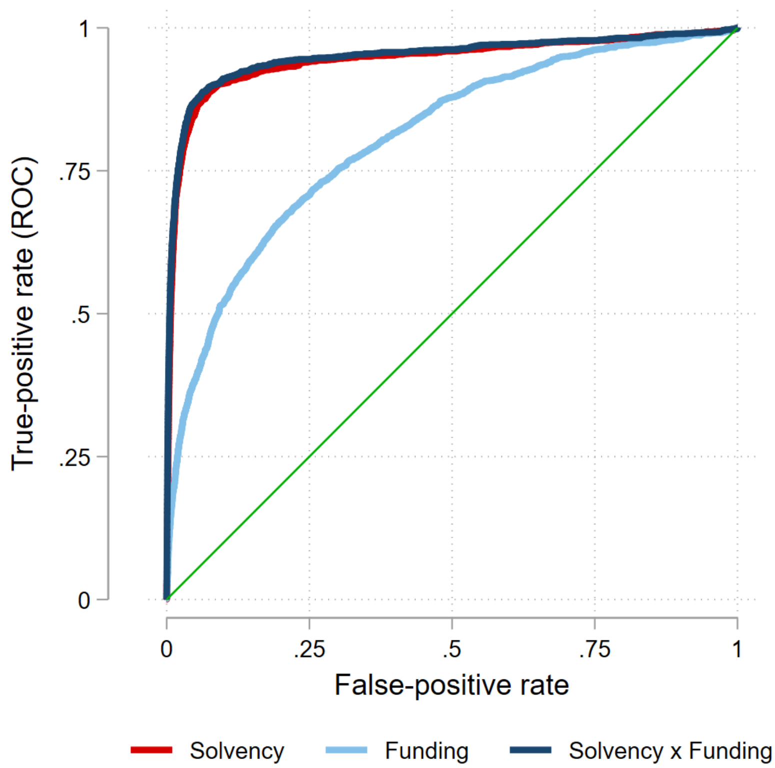
Notes: This figure plots the receiver operating characteristic (ROC) curve for the estimates based on columns (1) through (3) of Table 4.

Figure A.13: ***ROC Curves: 1929-1935 Sample***



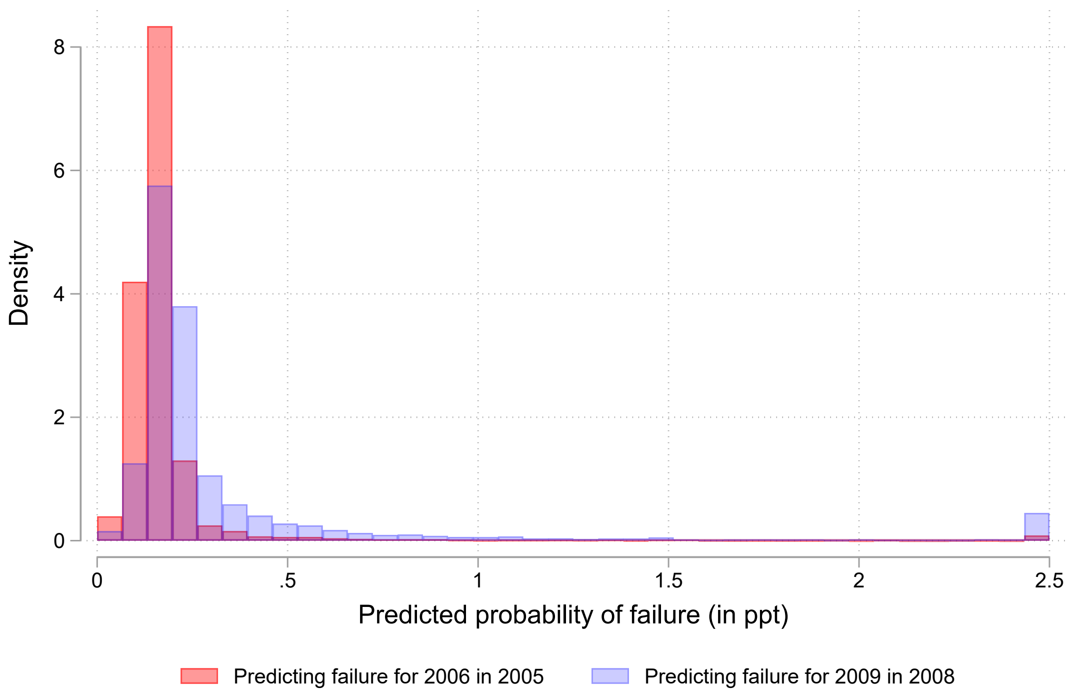
Notes: This figure plots the receiver operating characteristic (ROC) curve for the estimates based on columns (6) through (8) of Table 5.

Figure A.14: ***ROC Curves: 1959-2023 Sample***



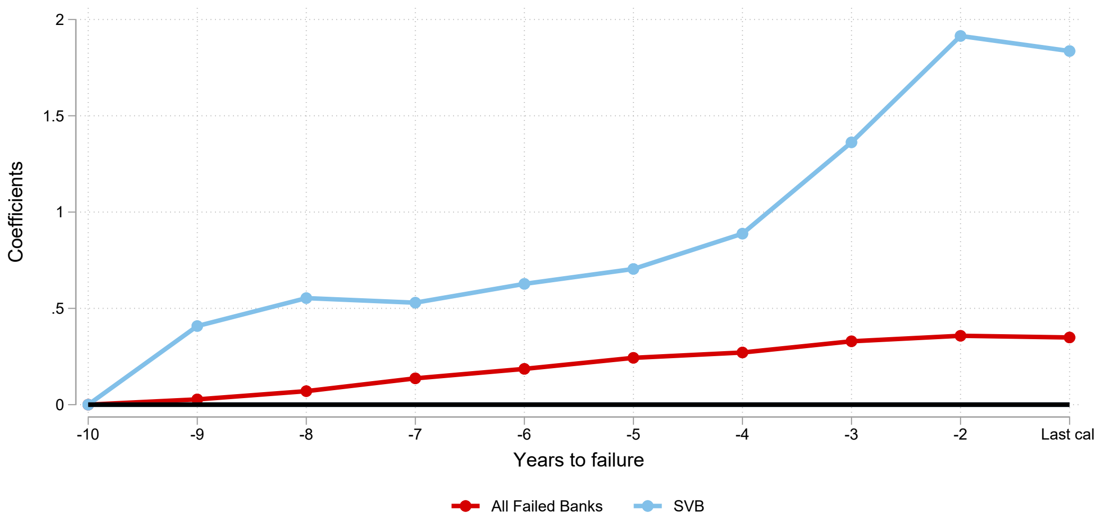
Notes: This figure plots the receiver operating characteristic (ROC) curve for the estimates based on columns (1) through (3) of Table 6.

Figure A.15: ***Distributions of predicted failure right in 2004 (before the GFC) and 2008 (GFC).***



Notes: This figure shows the distribution of the predicted failure probability in 2006 and 2009. Estimated using Logit. Predicted values are clipped at 2.5 percentage points.

Figure A.16: ***Assets in Failing banks (1959-2023) and SVB.***



Notes: Both panels shows the sequence of coefficients from a regression of the following form:

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

where y_{bt} is bank b's total assets, and α_b is a set of bank fixed effects. The sample is restricted to failing banks and to the ten years before they fail and banks that fail after 1959.

Table A.1: *Summary Statistics: Bank-level data from 1865 through 1941.*

	N	Mean	Std. dev.	1st	10th	25th	75th	90th	99th
Failing bank	339,689	0.20	0.40	0.00	0.00	0.00	0.00	1.00	1.00
Equity/assets	115,107	0.34	0.14	0.00	0.18	0.25	0.43	0.51	0.65
Loans/assets	110,796	0.55	0.13	0.20	0.37	0.46	0.64	0.71	0.80
Deposits/assets	111,119	0.46	0.18	0.07	0.21	0.33	0.59	0.69	0.81
Liquid assets/assets	115,107	0.19	0.11	0.00	0.08	0.12	0.25	0.33	0.52
NPL/loans	110,781	0.01	0.03	0.00	0.00	0.00	0.00	0.03	0.14
Wholesale funding/assets	115,107	0.01	0.04	0.00	0.00	0.00	0.00	0.04	0.18
Dividend payouts restricted	115,322	0.15	0.35	0.00	0.00	0.00	0.00	1.00	1.00
3-year asset growth	324,950	0.32	0.45	-0.59	-0.17	0.05	0.55	0.87	1.63

Notes: This table reports summary statistics for the bank-level data based on the OCCs annual report. Data are at annual frequency.

Table A.2: *Summary Statistics: Bank-level data from 1959 through 2023.*

	N	Mean	Std. dev.	1st	10th	25th	75th	90th	99th
Failing bank	2,479,740	0.06	0.24	0.00	0.00	0.00	0.00	0.00	1.00
Equity/assets	2,453,041	0.10	0.07	0.04	0.06	0.07	0.11	0.14	0.34
Loans/assets	2,477,072	0.55	0.16	0.11	0.34	0.45	0.66	0.75	0.88
Deposits/assets	2,479,701	0.86	0.10	0.44	0.79	0.85	0.91	0.92	0.94
Liquid assets/assets	2,479,701	0.36	0.16	0.04	0.16	0.25	0.47	0.58	0.78
Loans/assets	2,477,072	0.55	0.16	0.11	0.34	0.45	0.66	0.75	0.88
Deposits/assets	2,479,701	0.86	0.10	0.44	0.79	0.85	0.91	0.92	0.94
Liquid assets/assets	2,479,701	0.36	0.16	0.04	0.16	0.25	0.47	0.58	0.78
Time deposits/assets	2,436,567	0.36	0.16	0.00	0.12	0.25	0.48	0.55	0.67
Wholesale funding/assets	2,477,071	0.01	0.04	0.00	0.00	0.00	0.00	0.04	0.18
Brokered deposits/assets	1,461,833	0.01	0.05	0.00	0.00	0.00	0.00	0.03	0.22
Net income/assets	678,721	0.01	0.02	-0.03	0.00	0.01	0.01	0.02	0.03
NPL/loans	1,354,309	0.02	0.03	0.00	0.00	0.00	0.02	0.04	0.12
LLP/loans	564,425	0.01	0.39	-0.00	0.00	0.00	0.01	0.01	0.06
NIM	677,344	0.02	0.03	-0.02	-0.00	0.01	0.03	0.03	0.05
3-year asset growth	2,141,586	0.14	0.31	-0.38	-0.11	-0.01	0.22	0.41	1.31

Notes: This table reports summary statistics for the bank-level data based the FFIEC Call Report. Net income, Loan Loss Provisions (LLP), and net interest income are based on annual, end-of-year data. All other variables are quarterly. The net interest margin is calculated as the ratio of net interest income over total assets.

Table A.3: ***Uninsured Depositor Loss Rates in Bank Failures***.

Era	Number of Failures	Failures with Losses to Depositors (in %)	Conditional Loss Rate (in %)	Unconditional Loss Rate (in %)
Excess. Lending	83	0.49	0.33	0.23
External	239	0.78	0.57	0.53
Fraud	287	0.58	0.41	0.30
Governance	89	0.82	0.52	0.49
Losses	269	0.39	0.41	0.25
Run	20	0.03	0.18	0.08
Not classified	1870	0.43	0.54	0.53

Notes: Data on loss rates from 1992 through 2022 are from FDIC (2023)

Table A.4: ***Asset and Deposit Recovery***.

Dependent variable	Asset recovery	Deposit recovery
	(1)	(2)
Good	0.76***	
	(0.01)	
Doubtful	0.32***	
	(0.01)	
Worthless	0.25***	
	(0.02)	
Asset recovery		1.08***
		(0.01)
Recovered form Shareholders		0.29***
		(0.10)
N	2445	2240

Notes: Column (1) shows results from estimating the following regression:

$$\begin{aligned}\text{Total collected funds}_b = & \beta_1 \times \text{Assessed good}_b \\ & + \beta_2 \times \text{Assessed doubtful}_b \\ & + \beta_3 \times \text{Assessed worthless}_b + \epsilon_b,\end{aligned}$$

where all variables are normalized by total assets available in receivership and all RHS variables corresponds to the assessment of the receiver in a failed bank. Columns (2) shows results for estimating:

$$\begin{aligned}\frac{\text{Paid out to depositors}}{\text{Deposits}}_b = & \beta_1 \times \text{Total collected funds}_b + \\ & \beta_2 \times \text{Collected from Shareholders}_b + \epsilon_b,\end{aligned}$$

where Collected from Shareholders refers to the funds the receiver collects from shareholders after double liability is enforced and all RHS variables are normalized by total assets.

Table A.5: ***Predicting Bank Failures at Longer Horizons: 1863-1904***.

Dependent variable	Fail in 5 years				
	(1)	(2)	(3)	(4)	(5)
Solvency:					
- NPL/Loans	1.46**		1.20*		1.30**
	(0.72)		(0.62)		(0.62)
- Dividend Payout Restricted	0.22		0.18		0.20
	(0.18)		(0.18)		(0.18)
Funding:					
- Wholesale Funding/Assets		4.37***	4.12***		4.16***
		(1.15)	(1.21)		(1.22)
Solvency $\times$ ***Funding:***					
- NPL/Loans $\times$ WF/Assets			6.37		8.12
			(23.62)		(23.68)
Bank Growth:					
- Q1 of Growth from t-3 to t				0.03	-0.01
				(0.07)	(0.08)
- Q2 of Growth from t-3 to t				-0.11*	-0.12*
				(0.06)	(0.07)
- Q4 of Growth from t-3 to t				0.07	0.09
				(0.08)	(0.08)
- Q5 of Growth from t-3 to t				0.06	0.06
				(0.08)	(0.09)
Aggregate Conditions:					
- GDP Growth from t-3 to t				0.32	0.47**
				(0.21)	(0.21)
N	49799	49799	49799	53877	49761
No of Banks	4525	4525	4525	4902	4522
Mean of dep. var.	.32	.32	.32	.31	.32
AUC	0.646	0.670	0.690	0.630	0.703

Notes: This table presents estimates of (2) with failure in $t+5$ as the dependent variable for the 1863-1904 sample. In addition to the reported predictor variables, we also include the log of a bank's age. Standard errors in parentheses are clustered at the bank level; *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table A.6: ***Predicting Failure at Longer Horizons: 1914-1935.***

Dependent variable	Fail in 5 years									
Sample	1914-1928					1929-1935				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Solvency:										
- Equity/Assets	-8.19***		-5.65***		-7.42***	-6.81***		-6.71***		-5.84***
	(0.50)		(0.60)		(0.64)	(0.68)		(0.67)		(0.67)
- Surplus/Equity	-1.82***		-1.89***		-1.44***	1.61***		1.13***		1.17***
	(0.28)		(0.41)		(0.41)	(0.30)		(0.30)		(0.32)
- Div. Payout Restricted						-0.18		-0.14		-0.01
						(0.18)		(0.18)		(0.18)
- Loans/Assets	0.92*		0.93*		0.85*	3.87***		3.77***		3.29***
	(0.53)		(0.54)		(0.50)	(0.39)		(0.42)		(0.40)
Funding:										
- Time Deposits/Deposits		2.23***	2.35***		2.19***					
		(0.18)	(0.53)		(0.53)					
- Wholesale Funding/Assets							3.66***	-7.85***		-3.98**
							(1.05)	(1.81)		(1.78)
Solvency × ***Funding:***										
- Surplus/Equity × Time Dep./Dep.			-1.16		-1.64					
			(1.02)		(1.02)					
- Surplus/Eq. × WF/Assets								24.17***		22.14***
								(5.83)		(5.78)
Bank Growth:										
- Q1 of Growth from t-3 to t				0.37***	0.55***				-0.20	0.09
				(0.12)	(0.15)				(0.14)	(0.18)
- Q2 of Growth from t-3 to t				0.03	0.32**				-0.08	0.03
				(0.12)	(0.15)				(0.15)	(0.18)
- Q4 of Growth from t-3 to t				-0.27**	-0.21				-0.09	-0.09
				(0.11)	(0.14)				(0.15)	(0.18)
- Q5 of Growth from t-3 to t				0.03	0.05				-0.25*	-0.24
				(0.12)	(0.15)				(0.14)	(0.17)
Aggregate Conditions:										
- GDP Growth from t-3 to t				-1.59***	-1.83***				3.10***	3.51***
				(0.10)	(0.13)				(0.18)	(0.21)
N	69156	63137	62328	109163	62214	31134	31353	31078	39356	30979
No of Banks	9151	9066	9055	9429	9053	7369	7369	7363	7504	7359
Mean of dep. var.	.53	.56	.55	.57	.55	2.2	2.2	2.2	2.9	2.2
Sample	1914-1928	1914-1928	1929-1928	1914-1928	1914-1928	1929-1935	1929-1935	1929-1935	1929-1935	1929-1935
AUC	0.706	0.609	0.787	0.778	0.857	0.567	0.740	0.576	0.262	0.548

Notes: This table presents OLS estimates of (2) with failure in $t+5$ as the dependent variables for the 1914-1935 sample. Standard errors in parentheses are clustered at the bank level; *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table A.7: ***Predicting Failure: 1959-2023*.**

Dependent variable	Fail in five years				
	(1)	(2)	(3)	(4)	(5)
Solvency:					
- Net Income/Assets	-2.62***		0.36		0.37
	(0.46)		(0.30)		(0.34)
Funding:					
- Time Deposits/Deposits		1.20***	1.25***		1.12***
		(0.05)	(0.05)		(0.06)
Solvency* × *Funding:					
- Net Inc./Assets × Time Dep./Dep.			-8.35***		-10.65***
			(2.47)		(2.54)
Bank Growth:					
- Q1 of Growth from t-3 to t				0.09***	0.09***
				(0.02)	(0.02)
- Q2 of Growth from t-3 to t				-0.01	-0.01
				(0.02)	(0.02)
- Q4 of Growth from t-3 to t				0.10***	0.09***
				(0.02)	(0.02)
- Q5 of Growth from t-3 to t				0.45***	0.42***
				(0.02)	(0.02)
Aggregate Conditions:					
- GDP Growth from t-3 to t				1.43***	1.08***
				(0.09)	(0.09)
N	616298	614994	614928	606404	604984
No of Banks	22102	22108	22099	22085	22073
Mean of dep. var.	.26	.26	.26	.27	.26
AUC	0.553	0.699	0.701	0.699	0.754

Notes: This table presents estimates of (2) with failure in $t+5$ as the dependent variables for the 1959-2023 sample. In addition to the reported predictor variables, we also include the log of a bank's age. Standard errors in parentheses are clustered at the bank level; *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table A.8: ***Predicting Bank Failures: 1959-2023***.

Dependent variable	Fail in five years				
	(1)	(2)	(3)	(4)	(5)
Solvency:					
- Equity/Assets	-4.78***		3.24***		2.63***
	(0.16)		(0.15)		(0.14)
Funding:					
- Time Deposits/Deposits		2.18***	7.42***		8.73***
		(0.07)	(0.22)		(0.25)
- Eq./Assets $\times$ Time Dep./Dep.			-61.22***		-69.88***
			(1.81)		(2.05)
Bank Growth:					
- Q1 of Growth from t-3 to t				0.57***	0.70***
				(0.03)	(0.03)
- Q2 of Growth from t-3 to t				0.02	0.12***
				(0.01)	(0.01)
- Q4 of Growth from t-3 to t				0.02	-0.10***
				(0.01)	(0.02)
- Q5 of Growth from t-3 to t				0.12***	-0.12***
				(0.02)	(0.02)
Aggregate Conditions:					
- GDP Growth from t-3 to t				-1.33***	-4.39***
				(0.10)	(0.16)
N	610563	614994	609193	606404	599423
No of Banks	22065	22108	22062	22085	22036
Mean of dep. var.	.26	.27	.26	.27	.27
AUC	0.913	0.806	0.930	0.718	0.938

Notes: This table presents estimates of (2) with failure in $t+1$ as the dependent variables for the 1959-2023 sample. In addition to the reported predictor variables, we also include the log of a bank's age. Standard errors in parentheses are clustered at the bank level; *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table A.9: ***Predicting Bank Failures: 1863-1904***.

Dependent variable	Fail next year				
	(1)	(2)	(3)	(4)	(5)
Solvency:					
- NPL/Loans	6.50***		5.92***		5.13***
	(0.71)		(0.93)		(0.97)
- Dividend Payout Restricted	1.77***		1.58***		1.45***
	(0.16)		(0.16)		(0.17)
Funding:					
- Wholesale Funding/Assets		11.94***	10.98***		11.34***
		(0.73)	(0.86)		(0.87)
Solvency $\times$ ***Funding:***					
- NPL/Loans $\times$ WF/Assets			13.21		5.60
			(10.24)		(10.32)
Bank Growth:					
- Q1 of Growth from t-3 to t				1.54***	1.40***
				(0.25)	(0.28)
- Q2 of Growth from t-3 to t				0.82***	0.99***
				(0.27)	(0.30)
- Q4 of Growth from t-3 to t				0.65**	0.88***
				(0.27)	(0.30)
- Q5 of Growth from t-3 to t				0.39	0.65**
				(0.27)	(0.30)
Aggregate Conditions:					
- GDP Growth from t-3 to t				-2.79***	-1.76***
				(0.57)	(0.60)
N	49799	49799	49799	53877	49761
No of Banks	4525	4525	4525	4902	4522
Mean of dep. var.	.0047	.0047	.0047	.0046	.0047
AUC	0.776	0.791	0.846	0.730	0.854

Notes: This table presents estimates of (2) with failure in $t+1$ as the dependent variable for the 1865-1904 sample. Here, we estimate the model using Logit rather than OLS. In addition to the reported predictor variables, we also include the log of a bank's age. Standard errors in parentheses are clustered at the bank level; *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table A.10: *Predicting Bank Failures: 1914-1935 using Logit estimation.*

Dependent variable	Fail next year									
Sample	1914-1928					1929-1935				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Solvency:										
- Equity/Assets	-5.52***		-3.14***		-6.58***	-3.71***		-3.90***		-5.67***
	(0.93)		(1.02)		(1.10)	(0.68)		(0.70)		(0.74)
- Surplus/Equity	-7.80***		-8.82***		-6.56***	-3.39***		-2.98***		-2.30***
	(0.41)		(0.88)		(0.84)	(0.24)		(0.30)		(0.31)
- Div. Payout Restricted						0.52***		0.35***		0.29**
						(0.11)		(0.12)		(0.12)
- Loans/Assets	0.17***		0.18***		0.21***	4.52***		2.79***		2.74***
	(0.06)		(0.05)		(0.04)	(0.26)		(0.28)		(0.28)
Funding:										
- Time Deposits/Deposits		1.23***	1.32***		1.31***					
		(0.22)	(0.45)		(0.45)					
- Wholesale Funding/Assets							12.80***	9.29***		8.73***
							(0.45)	(0.85)		(0.88)
Solvency* $\times$ *Funding:										
- Surplus/Equity $\times$ Time Dep./Dep.			1.22		0.01					
			(1.67)		(1.61)					
- Surplus/Eq. $\times$ WF/Assets								2.01		1.94
								(2.53)		(2.55)
Bank Growth:										
- Q1 of Growth from t-3 to t				1.59***	1.28***				0.94***	0.81***
				(0.13)	(0.19)				(0.09)	(0.13)
- Q2 of Growth from t-3 to t				0.36**	0.37*				0.37***	0.38***
				(0.16)	(0.22)				(0.10)	(0.14)
- Q4 of Growth from t-3 to t				-0.51***	-0.25				-0.50***	-0.21
				(0.20)	(0.25)				(0.12)	(0.16)
- Q5 of Growth from t-3 to t				0.00	-0.25				-0.31***	-0.29*
				(0.17)	(0.24)				(0.11)	(0.16)
Aggregate Conditions:										
- GDP Growth from t-3 to t				-2.35***	-2.87***				-1.83***	-0.79***
				(0.22)	(0.29)				(0.15)	(0.21)
N	69156	63137	62328	109163	62214	31134	31353	31078	39356	30979
No of Banks	9151	9066	9055	9429	9053	7369	7369	7363	7504	7359
Mean of dep. var.	.0053	.0056	.0055	.0057	.0055	.022	.022	.022	.029	.022
AUC	0.728	0.627	0.819	0.772	0.882	0.752	0.771	0.816	0.774	0.835

Notes: This table presents Logit estimates of (2) with failure in $t+1$ as the dependent variable for the 1914-1935 sample. Columns (1) through (5) are estimated with using data from 1914-1928. In columns (6) through (10) we use data from 1929 through 1935. We split the sample due to changes in the reported line items in 1929. Standard errors in parentheses are clustered at the bank level; *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table A.11: ***Predicting Bank Failures: 1959-2023 using Logit estimation.***

Dependent variable	Fail in five years				
	(1)	(2)	(3)	(4)	(5)
Solvency:					
- Net Income/Assets	-57.07***		-19.52***		-17.86***
	(0.78)		(1.14)		(1.14)
Funding:					
- Time Deposits/Deposits		9.38***	6.73***		6.76***
		(0.19)	(0.22)		(0.22)
Solvency $\times$ ***Funding:***					
- Net Inc./Assets $\times$ Time Dep./Dep.			-71.63***		-64.61***
			(2.76)		(2.76)
Bank Growth:					
- Q1 of Growth from t-3 to t				1.79***	1.15***
				(0.09)	(0.10)
- Q2 of Growth from t-3 to t				0.16	0.10
				(0.12)	(0.12)
- Q4 of Growth from t-3 to t				0.19	0.21*
				(0.11)	(0.12)
- Q5 of Growth from t-3 to t				0.71***	0.48***
				(0.10)	(0.11)
Aggregate Conditions:					
- GDP Growth from t-3 to t				-5.02***	-1.51***
				(0.32)	(0.32)
N	616298	614994	614928	606404	604984
No of Banks	22102	22108	22099	22085	22073
Mean of dep. var.	.0027	.0027	.0027	.0027	.0027
AUC	0.945	0.809	0.937	0.721	0.942

Notes: This table presents estimates of (2) with failure in $t+1$ as the dependent variables for the 1959-2023 sample. Unlike in Table 6, we estimate (2) using Logit rather than OLS. In addition to the reported predictor variables, we also include the log of a bank's age. Standard errors in parentheses are clustered at the bank level; *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table A.12: ***Predicting Failure using Logit: 1865-1904***.

Dependent variable	Fail next year					Fail in 5 years				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Leverage & Losses:										
- Equity/Assets	-2.02***	-2.62***	-2.03***		-4.22***	-3.85***	-0.01***	-3.99***		-2.99***
	(0.50)	(0.51)	(0.51)		(0.58)	(0.55)	(0.00)	(0.57)		(0.67)
- NPL/Loans		8.12***			6.94***					4.56***
		(0.72)			(0.77)					(1.31)
- Wholesale Funding/Assets	12.37***	12.07***	12.35***		11.92***	8.33***	0.02***	8.28***		8.06***
	(0.63)	(0.65)	(0.64)		(0.68)	(0.93)	(0.00)	(0.93)		(0.97)
- Dividend Payout Restricted	1.77***	1.49***	1.77***		1.39***	0.30	0.00	0.30		0.21
	(0.14)	(0.15)	(0.14)		(0.15)	(0.28)	(0.00)	(0.28)		(0.29)
Bank Growth:										
- Q1 of Growth from t-3 to t				1.25***	1.09***				0.14	0.22
				(0.20)	(0.21)				(0.22)	(0.22)
- Q2 of Growth from t-3 to t				0.48**	0.58**				-0.51**	-0.39
				(0.22)	(0.23)				(0.26)	(0.26)
- Q4 of Growth from t-3 to t				0.42*	0.22				0.32	0.20
				(0.22)	(0.23)				(0.21)	(0.21)
- Q5 of Growth from t-3 to t				0.73***	0.04				0.64***	0.20
				(0.21)	(0.22)				(0.20)	(0.21)
Aggregate Conditions:										
- GDP Growth from t-3 to t				-3.42***	-3.25***				1.45**	1.16*
				(0.49)	(0.52)				(0.57)	(0.61)
N	94553	94332	94332	86120	85978	94553	94332	94332	86120	85978
No of Banks	5439	5431	5431	5351	5344	5439	5431	5431	5351	5344
Mean of dep. var.	.0035	.0035	.0035	.0037	.0037	.0028	.0028	.0028	.0028	.0028
AUC	0.806	0.822	0.806	0.651	0.837	0.703	0.711	0.702	0.610	0.718

Notes: This table shows results from estimating a regression of the following form:

$$\text{Failure}_{bt+s} = \alpha + \beta_1 \times \frac{\text{Equity}}{\text{Assets}}_{bt} + \beta_2 \times \frac{\text{NPL}}{\text{Loans}}_{bt} + \beta_3 \times \frac{\text{Wholesale Funding}}{\text{Assets}}_{bt} + \beta_4 \times \text{GDP Growth}_t + \sum_{k=1}^{5} \beta_{5,k} \times [\text{Growth}_{bt} \in Q_k] + \epsilon_{bt},$$

where Failure_{bt+s} is a dummy that indicates whether bank b fails in year $t+s$. Unlike in Table 4, estimate the model using Logit and not OLS. Next to the reported control variable we also include the log of a bank's age as a control variable. Standard errors in parentheses are clustered at the bank level; *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table A.13: ***Predicting Failure using Logit: 1959-2023***.

Dependent variable	Fail next year					Fail in 5 years				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Leverage & Losses:										
- Equity/Assets	-101.07***					-11.18***				
	(1.19)					(1.04)				
- Net Income/Assets		-56.99***			-51.89***		-8.40***			-10.60***
		(0.78)			(0.82)		(1.11)			(1.08)
- NPL/Loans			24.82***					4.12***		
			(0.37)					(0.62)		
Bank Growth:										
- Q1 of Growth from t-3 to t				1.78***	1.16***				0.45***	0.40***
				(0.09)	(0.10)				(0.09)	(0.09)
- Q2 of Growth from t-3 to t				0.16	0.11				-0.08	-0.08
				(0.12)	(0.12)				(0.11)	(0.11)
- Q4 of Growth from t-3 to t				0.19	0.22*				0.49***	0.49***
				(0.11)	(0.12)				(0.09)	(0.09)
- Q5 of Growth from t-3 to t				0.71***	0.60***				1.41***	1.41***
				(0.10)	(0.11)				(0.08)	(0.08)
Aggregate Conditions:										
- GDP Growth from t-3 to t				-5.07***	-2.27***				5.07***	5.24***
				(0.32)	(0.32)				(0.30)	(0.30)
N	610563	616298	325664	606404	606344	610563	616298	325664	606404	606344
No of Banks	22065	22102	19244	22085	22076	22065	22102	19244	22085	22076
Mean of dep. var.	.0026	.0027	.0042	.0027	.0027	.0026	.0026	.0026	.0027	.0027
AUC	0.945	0.809	0.937	0.721	0.942					

Notes: This table shows results from estimating a regression of the following form:

$$\text{Failure}_{bt+s} = \alpha + \beta_1 \times \frac{\text{Equity}}{\text{Assets}}_{bt} + \beta_2 \times \frac{\text{Income}}{\text{Assets}}_{bt} + \beta_3 \times \frac{\text{NPL}}{\text{Loans}}_{bt} + \beta_4 \times \text{GDP Growth}_t + \sum_{k=1}^{5} \beta_{5,k} \times [\text{Growth}_{bt} \in Q_k] + \epsilon_{bt},$$

where Failure_{bt+s} is a dummy that indicates whether bank b fails in year $t+s$. Unlike in Table 6, estimate the model using Logit and not OLS. Next to the reported control variable we also include the log of a bank's age as a control variable. Standard errors in parentheses are clustered at the bank level; *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table A.14: ***Area Under the Curve by era and during major waved of bank failures/banking crises.***

Panel A: 1865-1935						
	1890	1893	1890-1896	1930-1933	1929-1931	1932-1933
AUC	0.903	0.876	0.853	0.791	0.737	0.861
Panel B: 1959-2023						
	Boring Banking	S&L and Dereg.	Global Financial Crisis	Post-Crisis	1884-1992	2007-2013
AUC	0.873	0.945	0.949	0.851	0.944	0.946

Notes: This table reports the area under the receiver operating characteristics curve (AUC) by sample period. In the first three columns of Panel A, we use in-sample predictions based on the estimation using data from 1889 through 1904 that corresponds to column (3) of Table 4. In the last three columns of panel A, we use in-sample predictions based on the estimation using data from 1929-1935 in column (8) of Table 5. In Panel B, we calculate the AUC based on the predictions based obtained from the model in column (1) of Table 6.

B Data Appendix

B.1 Appendix B1: Call Reports:

OCC Annual Report to Congress:1965 through 1941 We use two main data sources on bank balance sheets. Data on national bank balance sheets from 1863 through 1941 are from the Office of the Comptroller of the Currency's (OCC) Annual Report to Congress.

Note that the format of the tables changes in 1905. Starting in 1905, balance sheets for multiple banks are reported in tables that go across two pages. Figure B.2 shows an example of the format after 1905 form the annual report to congress of 1933. We digitze these data also using the techniques discussed in Correia and Luck (2023).

Figure B.1: *Example of a Balance Sheet Reported in the OCC's Annual Report to Congress from 1900.*

338 REPORT OF THE COMPTROLLER OF THE CURRENCY.

KENTUCKY.

Farmers' National Bank, Augusta.

JOHN M. HARBESON, *President.* No. 4612. BEN HARBESON, *Cashier.*

Resources.		Liabilities.	
Loans and discounts	$113,507.83	Capital stock paid in	$50,000.00
Overdrafts	1,251.06	Surplus fund	4,450.00
U. S. bonds to secure circulation	16,250.00	Undivided profits, less current expenses and taxes paid	2,249.16
U. S. bonds to secure deposits		National-bank notes outstanding	16,250.00
U. S. bonds on hand	100.00	State-bank notes outstanding	
Premiums on U. S. bonds	15.00	Due to other national banks	1,126.08
Stocks, securities, etc	22,625.00	Due to State banks and bankers	258.93
Bank'ghouse, furniture, and fixtures	1,000.00	Due to trust companies and savings banks	
Other real estate and mortg's owned	1,800.00	Due to approved reserve agents	
Due from other national banks	11,444.74	Dividends unpaid	
Due from State banks and bankers		Individual deposits	260,480.44
Due from approved reserve agents	142,627.00	United States deposits	
Internal-revenue stamps	356.32	Deposits of U.S. disbursing officers	
Checks and other cash items	43.25	Notes and bills rediscounted	
Exchanges for clearing house		Bills payable	
Bills of other national banks	6,490.00	Liabilities other than those above stated	1,100.75
Fractional currency, nickels, cents	33.66		
Specie	9,059.00		
Legal-tender notes	8,500.00		
U. S. certificates of deposit			
Redemption fund with Treas. U. S.	812.50		
Due from Treasurer U. S.			
Total	335,915.36	Total	335,915.36

Figure B.2: *Example of a Balance Sheet Reported in the OCC's Annual Report to Congress from 1933.*

Assets and liabilities of national banks as shown by reports of condition December 30, 1933—Continued

ILLINOIS—Continued

DISTRICT NO. 8—Continued

	Location and name of bank	President	Cashier	Loans and discounts, including overdrafts	United States Government securities owned	Other bonds, stocks, and securities, etc., owned
1	National City, National Stock Yards.	O. J. Sullivan	R. D. Garvin	$3, 664, 800	$6, 532, 834	$733, 004
2	New Douglas, Prange	A. F. Prange	W. W. Prange	107, 457	50, 000	64, 219
3	Oblong, First	S. F. Odell	J. B. McKnight	786, 318	83, 500	208, 704
4	O'Fallon, First	E. H. Smiley	W. R. Dorris	296, 662	174, 207	484, 832
5	Okawville, First	W. G. Frank	W. E. Friend	151, 758	79, 547	307, 394
6	Okawville, Old Exchange	C. H. Merrick	F. Moehle	88, 300	76, 675	216, 049
7	Pittsfield, First	L. C. King	F. A. Hicks	650, 876	251, 425	166, 315
8	Ramsey, Ramsey	L. C. Thiele	J. E. Easterday	137, 655	51, 250	43, 077
9	Raymond, First	J. E. McDavid	C. McNaughton	431, 989	35, 588	116, 659
10	Robinson, Second	A. U. McCandless	A. H. Lodge	1, 190, 820	485, 556	327, 905
11	St. Francisville, Peoples	S. Gray	G. H. Corrie	170, 068	107, 500	110, 128
12	Salem, Salem	J. C. Martin	A. H. Bachman	353, 021	968, 786	1, 324, 844
13	Sandoval, First	B. F. Holmes	H. H. Bellamy	58, 831	45, 710	28, 768
14	Smithton, First	J. A. Miller	E. P. Baltz	113, 288	59, 881	80, 845
15	Sorento, National	L. C. Dreiling	H. H. Holbrook	10, 902	....	9, 491
16	Sparta, First	T. B. Stephenson	P. G. Brown	168, 354	95, 550	53, 236
17	Staunton, Staunton	C. F. Hackman	J. W. P. Kerr	85, 469	82, 293	237, 000
18	Sumner, First	G. W. Hill	O. D. Atkins	38, 933	59, 787	148, 707
19	Vandalia, First	F. L. Rice	R. H. Sturgess	234, 469	428, 738	170, 332
20	Vienna, First	W. L. Williams	F. E. Worrell	213, 432	100, 181	33, 951
21	Waterloo, First	N. B. Pautler	J. F. Schmidt	172, 706	223, 338	136, 773
22	Wayne City, First	J. F. Mateer	W. O. Allen	88, 400	52, 700	33, 908
23	White Hall, White Hall	C. A. Ruckel	R. S. Worcester	371, 118	206, 063	188, 280
24	Witt, Security	H. F. Fesser	H. S. Armentrout	121, 245	64, 346	138, 243
25	Woodlawn, First	E. A. Hill	M. Wood	68, 828	47, 522	44, 461
26	Wood River, First	O. F. Nagel	G. G. Guker	237, 024	92, 269	170, 906
27	Wood River, Wood River	J. M. Olin	H. E. Paton	261, 407	....	55, 577
28	Worden, First	T. C. Unger	W. E. Meyer	38, 797	33, 308	10, 941
29	Xenia, First	J. M. Tully	E. Kepp	99, 489	34, 000	1, 169
30	Zeigler, First	F. G. Hitt	R. R. Frazier	49, 690	396, 574	220, 202

Cash and exchange including reserve with Federal Reserve bank	Other assets	Total assets	Capital	Surplus	Undivided profits	Total deposits	Circulation	Bills payable and rediscounts	Other liabilities	
$3, 678, 840	$123, 007	$14, 732, 491	$750, 000	$150, 000	$45, 440	$12,983,612	$750, 000	....	$53, 439	1
16, 019	4, 386	242, 081	25, 000	10, 000	837	206, 244	....	....	....	2
210, 440	76, 380	1, 365, 342	75, 000	50, 000	21, 563	1, 144, 859	73, 860	....	60	3
183, 751	75, 195	1, 214, 647	100, 000	30, 000	4, 676	979, 939	100, 000	....	32	4
44, 503	5, 173	588, 375	50, 000	10, 000	7, 526	470, 830	50, 000	....	19	5
67, 929	4, 889	453, 842	50, 000	10, 000	14, 951	328, 891	50, 000	....	....	6
206, 835	113, 931	1, 389, 382	125, 000	125, 000	41, 325	998, 602	99, 280	....	175	7
68, 692	14, 762	315, 436	25, 000	25, 000	7, 675	232, 761	25, 000	....	....	8
34, 659	41, 646	660, 541	50, 000	10, 000	763	494, 282	25, 000	$80, 496	....	9
432, 586	67, 348	2, 504, 215	150, 000	37, 500	33, 989	2, 188, 976	93, 750	....	....	10
34, 200	19, 456	441, 352	70, 000	10, 000	5, 723	305, 624	50, 000	....	5	11
360, 591	71, 420	3, 078, 662	100, 000	24, 000	56, 830	2, 822, 645	75, 000	....	187	12
49, 091	24, 437	206, 837	40, 000	2, 500	1, 301	138, 354	24, 640	....	42	13
25, 757	16, 668	296, 439	25, 000	8, 000	350	238, 032	25, 000	....	57	14
30, 302	5, 532	56, 227	25, 000	1, 850	(d) 7, 631	33, 982	....	3, 000	26	15
178, 157	30, 215	525, 512	50, 000	25, 000	11, 078	389, 401	50, 000	....	33	16
64, 862	15, 841	485, 465	50, 000	10, 000	26, 387	349, 032	50, 000	....	46	17
81, 973	8, 685	338, 085	25, 000	5, 000	674	281, 707	25, 000	....	704	18
202, 289	68, 789	1, 104, 597	100, 000	25, 000	19, 369	860, 078	100, 000	....	150	19
57, 696	59, 123	464, 383	60, 000	25, 000	2, 812	317, 130	59, 340	....	101	20
100, 669	6, 336	639, 872	25, 000	15, 000	1, 437	573, 435	25, 000	....	....	21
35, 121	33, 126	243, 255	45, 000	....	1, 436	171, 768	25, 000	....	51	22
121, 473	16, 158	903, 112	100, 000	20, 000	29, 480	703, 632	50, 000	....	....	23
27, 591	7, 947	350, 372	25, 000	5, 000	5, 248	299, 124	25, 000	....	....	24
95, 669	9, 520	266, 000	35, 000	2, 000	3, 282	200, 718	25, 000	....	....	25
123, 661	50, 285	674, 145	50, 000	50, 000	2, 571	521, 416	50, 000	....	158	26
129, 894	69, 034	515, 912	60, 000	30, 000	10, 786	415, 126	....	....	....	27
18, 348	11, 710	113, 104	25, 000	5, 000	194	57, 912	24, 998	....	....	28
52, 560	14, 866	202, 084	25, 000	....	1, 082	150, 963	25, 000	....	39	29
116, 201	46, 553	829, 220	35, 000	7, 000	23, 940	729, 280	34, 000	....	....	30

B.1.1 FFIEC 010 and FFIEC 013: 1959 through 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 FRS, the FDIC, and the OCC. Figure B.3 shows an example of the balance sheet reporting form used in 1967. Figure B.4 shows an example of the income statement reporting form of the same year.

We document the construction of our variables from the various line items in table Table B.1.

Table B.1: *Definitions of FFIEC 010 and 013 line items.*

Item	Series	Item Number	Valid Period
Assets	RCON	2170	1959–12–31 to present
Equity	RCON	3210	1959–12–31 to present
Deposits	RCON	2200	1959–12–31 to present
Loans	RCON	1400	1959–12–31 to present
		2122	1976–03–31 to present
Cash	RCON	0010	1959–12–31 to present
Securities	RCON	0400 + 0600 + 0900 + 0950	1959–06–10 to 1976–03–31
		0390	1976–03–31 to 1993–12–31
		1754 + 1773	1994–03–31 to present
C&I loans	RCON	1600	1959–12–31 to 1984–03–31
		1766	1984–03–31 to present
Real Estate Loans	RCON	1410	1959–12–31 to present
Consumer Loans	RCON	1975	1959–12–31 to present
Credit Card Loans	RCON	2008	1967–12–31 to 2000–12–31
		B538	2001–03–31 to present
Financial Loans	RCON	1495	1959–06–10 to 1983–12–31
		1505 + 1510 + 1517 + 1756 +1757	1976–03–31 to 2000–12–31
		B531 + B534 + B535	2001–03–31 to present
Time Deposits	RCON	2514	1961–04–12 to 1983–12–31
	RCON	2604 + 6648	1984–03–31 to 2009–12–31
	RCON	J473 + J474 + 6648	2010–03–31 to present
Demand Deposits	RCON	2210	1959–12–31 to present
Brokered Deposits	RCON	2365	1983–09–30 to present
Insured Deposits	RCON	2702	1983–06–30 to 2006–03–31
	RCON	F045 + F049	2006–06–30 to present
Uninsured Deposits	RCON	2710 - (2722*100)	1983–06–30 to 1992–12–31
	RCON	5597	1993–03–31 to present
Loan Loss Provisions	RCON	4230	1969–12–31 to present
Net Income	IADX	5106	1960–12–31 to 1968–12–31
	RIAD	4340	1969–12–31 to present
Non-Performing Loans	RCON	1403 + 1407	1982–12–31 to present
Total Interest Income	RIAD	4107	1984–03–31 to present
Total Interest Expenses	RIAD	4170 + 4180 + 4190 + 4200	1969–12–31 to 1978–09–30
	RIAD	4170 + 4180 + 4185 + 4200	1978–12–31 to 1983–12–31
	RIAD	4073	1984–03–31 to present
Salaries and Employee Benefits	RIAD	4135	1969–12–31 to present
Number of Full-Time Employees	RIAD	4150	1969–12–31 to present

Figure B.3: *Example of FFIEC 010 Reporting Form from 1967.*

December 30, 1967 - December 31, 1968

Form F.R. 105 — Call 186 (Rev. 12-47)

Budget Bureau No. 55-R004

RCRI
RCON

> **Please read carefully "Instructions for the Preparation of Report of Condition"**—Every item and schedule must be filled in. Printed items must not be amended. Amounts that cannot properly be included in the printed items must be entered under "Other assets" or "Other liabilities."

DIST-ST-BANK 9000

Report of Condition of 9010
(Legal title of bank)

of 9130 (City), (County), (State) (Zip Code), **at the close of business on** 9999, **19**

State Bank No. 9020 *Federal Reserve District No.* 9170

ASSETS		Dollars		Cts.	
1. Cash, balances with other banks, and cash items in process of collection (Schedule D, item 7)		0010			1
2. United States Government obligations		0400			2
3. Obligations of States and political subdivisions		0900			3
4. Securities of Federal agencies and corporations		0600			4
5. Other securities (including $ corporate stocks)		0950			5
6. Federal funds sold and securities purchased under agreements to resell		1350			6
7. Other loans and discounts (Schedule A, item 10)		1400			7
8. Bank premises, furniture and fixtures, and other assets representing bank premises		2145			8
9. Real estate owned other than bank premises		2150			9
10. Customers' liability to this bank on acceptances outstanding	2153	2155			10
11. Other assets (item 6 of "Other assets" schedule)		2160			11
12. TOTAL ASSETS		2170			12
LIABILITIES					
13. Demand deposits of individuals, partnerships, and corporations (Schedule E, item 4)	2615	2220			13
14. Time and savings deposits of individuals, partnerships, and corporations (Schedule F, item 6)		2360			14
15. Deposits of United States Government (Schedule E, item 5 and Schedule F, item 7)		2610			15
16. Deposits of States and political subdivisions (Schedule E, item 6 and Schedule F, item 8)		2620			16
17. Deposits of foreign governments and official institutions, central banks and international institutions (Schedule E, item 7 and Schedule F, item 9)		2650			17
18. Deposits of commercial banks (Schedule E, items 8 and 9 and Schedule F, items 10 and 11)	2645	2660			18
19. Certified and officers' checks, etc. (Schedule E, item 10)		2330			19
20. TOTAL DEPOSITS (items 13 to 19) $	2200	xxx xxx	xxx	xx	20
(a) Total demand deposits (Schedule E, item 11) $	2210	xxx xxx	xxx	xx	(a)
(b) Total time and savings deposits (Schedule F, item 12) $	2350	xxx xxx	xxx	xx	(b)
21. Federal funds purchased and securities sold under agreements to repurchase		2800			21
22. Other liabilities for borrowed money		2850			22
23. Acceptances executed by or for account of this bank and outstanding	2915	2920			23
24. Other liabilities (item 7 of "Other liabilities" schedule) (including $ mortgages and other liens on bank premises and other real estate)		2930			24
25. TOTAL LIABILITIES		2950			25
CAPITAL ACCOUNTS					
26. (a) Capital notes and debentures		3200			26 (a)
(b) Preferred stock—total par value (No. shares outstanding)		3220			(b)
(c) Common stock—total par value (No. shares authorized) (No. shares outstanding)	3210	3230			(c)
27. Surplus		3240			27
28. Undivided profits		3250	3247		28
29. Reserve for contingencies and other capital reserves		3260			29
30. TOTAL CAPITAL ACCOUNTS		3270			30
31. TOTAL LIABILITIES AND CAPITAL ACCOUNTS		3300			31

Figure B.4: *Example of FFIEC 013 Reporting Form from 1967.*

December 31, 1978 - December 31, 1982

RCRI
RIAD

Consolidated Report of Income of ____________________
Legal Title of Bank

For period ending on ____________________, 19___

Section A - Sources and Disposition of Income

Dollar Amount in Thousands		Year-to-date Mil Thou	
1. OPERATING INCOME:			
a. Interest and fees on loans		4010	1.a.
b. Interest on balances with depository institutions		4115	1.b.
c. Income on Federal funds sold and securities purchased under agreements to resell in domestic offices of the bank and of its Edge and Agreement subsidiaries		4020	1.c.
d. Interest on U.S. Treasury securities	4027	4030	1.d.
e. Interest on obligations of other U.S. Government agencies and corporations		4040	1.e.
f. Interest on obligations of States and political subdivisions in the U.S.		4050	1.f.
g. Interest on other bonds, notes, and debentures	4060	4061	1.g.
h. Dividends on stock		4063	1.h.
i. Income from lease financing		4065	1.i.
j. Income from fiduciary activities		4070	1.j.
k. Service charges on deposit accounts in domestic offices		4080	1.k.
l. Other service charges, commissions, and fees		4090	1.l.
m. Other operating income (from Section D, item 4)		4100	1.m.
n. TOTAL OPERATING INCOME (sum of items 1a thru 1m)		4000	1.n.
2. OPERATING EXPENSES:			
a. Salaries and employee benefits		4135	2.a.
b. Interest on time certificates of deposit of $100,000 or more issued by domestic offices		4174	2.b.
c. Interest on deposits in foreign offices	4170	4172	2.c.
d. Interest on other deposits		4176	2.d.
e. Expense of Federal funds purchased and securities sold under agreements to repurchase in domestic offices of the bank and of its Edge and Agreement subsidiaries		4180	2.e.
f. (1) Interest on demand notes (note balances) issued to the U.S. Treasury	4185	4195	2.f.(1)
(2) Interest on other borrowed money		4190	2.f.(2)
g. Interest on subordinated notes and debentures		4200	2.g.
h. (1) Occupancy expense of bank premises, Gross	4210		2.h.(1)
(2) Less: Rental income	4215		2.h.(2)
(3) Occupancy expense of bank premises, Net	4217	4205	2.h.(3)
i. Furniture and equipment expense		4220	2.i.
j. Provision for possible loan losses (from Section C, item 4)		4230	2.j.
k. Other operating expenses (from Section E, item 3)		4240	2.k.
l. TOTAL OPERATING EXPENSES (sum of items 2a thru 2k)		4130	2.l.
3. INCOME BEFORE INCOME TAXES AND SECURITIES GAINS OR LOSSES (item 1n minus 2l)		4250	3.
4. APPLICABLE INCOME TAXES		4260	4.
5. INCOME BEFORE SECURITIES GAINS OR LOSSES (item 3 minus 4)		4270	5.
6. a. SECURITIES GAINS (losses), GROSS	4280		6.a.
b. APPLICABLE INCOME TAXES	4285		6.b.
c. SECURITIES GAINS (losses), NET		4290	6.c.
7. NET INCOME (item 5 plus or minus 6c)		4300	7.
OR			
7. INCOME BEFORE EXTRAORDINARY ITEMS		4300	7.
8. EXTRAORDINARY ITEMS, NET OF TAX EFFECT (From Section F, item 2c)		4320	8.
9. NET INCOME (item 7 plus or minus 8)		4340	9.

4025

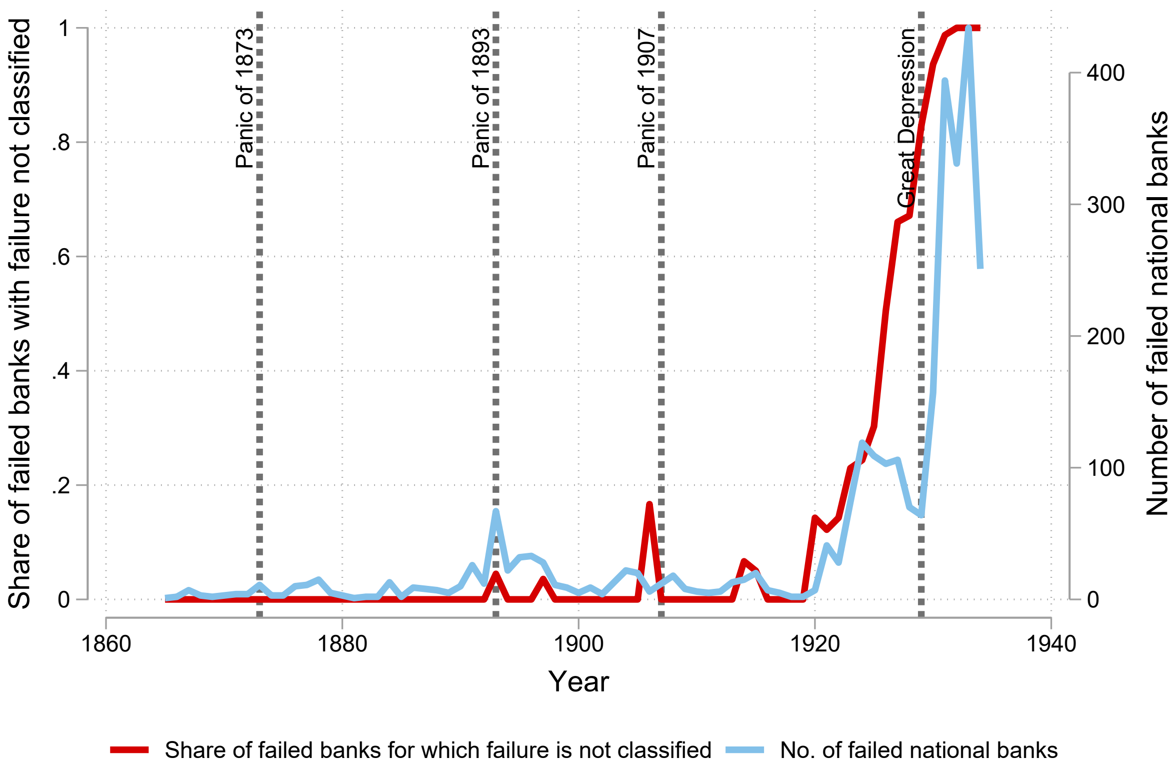
B.2 Causes of Failures as Classified By the OCC

We group the detailed cause of failure classifications by the OCC into one the following broad categories:

- **Excessive lending:** Excessive lending refers to a bank lending more than 10% of its paid-in capital to a single counterparty, which was not permitted by the national banking act.
- **External:** We classify failure as caused by external factors whenever the OCC cited the trigger of failure being related to things outside of a banks control such as crop losses, a deterioration of local economic conditions, robbery, or other shocks.
- **Fraud:** We classify a failure as due to fraud when the OCC cited misbehavior from bankers as the cause of failure. Fraud can be related to dishonesty of a bank employee or owner and excessive loans to insiders.
- **Governance:** We classify a failure being due to governance issues if bad management practices are cited as the cause of failure
- **Losses:** We refer to the cause of failure being due to losses when the bank is subject to losses or unable to realize on assets, injudicious banking practices, or depleted reserves.
- **Run:** We classify a run as being the cause of failure when the OCC reports the bank was closed by a run or anticipation of a run or heavy withdrawals.

Table B.2 shows the detailed mappings.

Figure B.5: ***Classification of causes of failure by the OCC across time.***



Notes: This figure shows the share of failed national banks for which the OCC provided a cause of failure (left y-axis) and the number of failed national banks (right y-axis) from 1863 through 1935.

Table B.2: ***OCC Causes of Failure Classification***.

OCC Cause of Failure	*Simplified Label*
Excessive loans and failure of large debtors	Excessive lending
Excessive loans to others, injudicious banking, and depreciation of securities	Excessive lending
Excessive loans	Excessive lending
Failure of large debtors	Excessive lending
Excessive loans to others and depreciation of securities	Excessive lending
Excessive loans to officers and directors	Excessive lending
Excessive loans to others and investments in real estate and mortgages	Excessive lending
Robbery and burning of bank	External
Crop loss	External
Deflation	External
Local financial conditions	External
Local financial depression from unforeseen agricultural or industrial disaster	External
Crop loss and depreciation of securities	External
Wrecked by assistant cashier	Fraud
Dishonesty of an officier of employee and local financial depression from unforeseen agricultural or industrial disaster	Fraud
Irregularities of president and speculation in real estate	Fraud
Dishonesty of an officier of employee	Fraud
Defalcation of officers and excessive loans to others	Fraud
Wrecked by the cashier	Fraud
Forgeries and embezzlement	Fraud
Defalcation of officers and fraudulent management	Fraud
Defalcation by former cashier	Fraud

Dishonesty	Fraud
Fraudulent management and depreciation of securities	Fraud
Fraudulent management, injudicious banking, investments in real estate and mortgages, and depreciation of securities	Fraud
Fraudulent management and closed by run	Fraud
Fraudulent management and local financial conditions	Fraud
Wrecked by president	Fraud
Fraudulent management	Fraud
Wrecked by cashier and president and by excessive loans to themselves	Fraud
Fraudulent management, defalcation of officers, and depreciation of securities	Fraud
Wrecked by defalcation by bookkeeper	Fraud
Fraudulent management	Fraud
Defalcation of officers and depreciation of securities	Fraud
Defalcation of officers	Fraud
Defalcation by cashier	Fraud
Fraudulent management, excessive loans to officers and directors, and excessive loans to others	Fraud
Excessive loans to officers and directors and depreciation of securities	Fraud
Irregularities	Fraud
Fraudulent management and injudicious banking	Fraud
Excessive loans to officers and directors and investments in real estate and mortgages	Fraud
Fraudulent management, excessive loans to officers and directors, and depreciation of securities	Fraud
Incompetent management	Governance

Incompetent management and local financial depression from unforeseen agricultural or industrial disaster	Governance
Incompetent management and dishonesty of an officier of employee	Governance
Bad management	Governance
Receiver appointed to levy and collect stock assessment covering deficiency in value of assets sold	Losses
Bad paper	Losses
Large losses and defalcation	Losses
Large losses	Losses
Deficient reserve and unable to realize on loans	Losses
General stringency of the money market, shrinkage in values, and imprudent methods of banking	Losses
Large losses and injudicious banking	Losses
Injudicious banking and depreciation of securities	Losses
Injudicious banking and failure of large debtors	Losses
Injudicious banking and adverse business conditions	Losses
Large losses in loans and discounts	Losses
Unable to realize on loans	Losses
Depreciation of securities	Losses
Injudicious banking	Losses
Receiver appointed to assess stockholders	Losses
Formerly in voluntary liquidation	Losses
Investments in real estate and mortgages and depreciation of securities	Losses
Depleted reserve	Losses
Large losses, withdrawals, and insufficient credit	Losses
Investment in real estate mortgages and depreciation of securities	Losses
Insufficient credit	Losses

Bad paper taken over from old organization	Losses
Depleted reserve and shrinkage of deposits	Losses
Unable to realize on assets	Losses
Receiver appointed after sale of assets, and stockholders to vote to place bank in liquidation	Losses
Receiver appointed to levy and collect stock assessment covering deficiency in value of assets sold, or to complete unfinished liquidation	Losses
Receiver appointed after voluntary liquidation	Losses
Injudicious banking and excessive loans to officers and others	Losses
Unable to realize on loans and failure of stockholders to pay balance due on capital	Losses
Information not available	No information
Temporary suspension	Other
Temporary suspension to adjust settlement on adverse judgment	Other
Large demands and depleted cash	Run
Inability to meet demands	Run
Local financial conditions and closed by run	Run
Heavy withdrawals	Run
Heavy withdrawals and lack of public confidence	Run
Directors closed due to rumor of run	Run
Closed by run	Run
Closed by directors in anticipation of run	Run