# Failing Banks

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**Abstract**

Why do banks fail? We create a panel covering most commercial banks from 1863 through 2023 and study the history of failing banks in the United States. Failing banks are characterized by rising asset losses. Losses are typically preceded by rapid lending growth, financed by non-core funding. Bank failures, including those that involve depositor runs, are highly predictable based on bank fundamentals, even in the absence of deposit insurance and a central bank. We construct a new measure of systemic risk using bank-level fundamentals and show that it forecasts the major waves of banking failures in U.S. history. Altogether, our evidence suggests that failures caused by runs on healthy banks are uncommon. Rather, the ultimate cause of bank failures and banking crises is almost always and everywhere 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 to 1934 and 14.5% of all commercial banks in existence from 1935 to 2023 failed at some point during the same period. 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 cited as 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, 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 determinants 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 around 38,000 distinct banks, of which more than 4,500 fail. This rich sample thus covers failures both before and after the founding of the Federal Reserve System and the introduction of deposit insurance. Hence, this sample allows us to also study bank failures during historical episodes in which bank runs can in principle have been a common cause of bank failures.

Our analysis proceeds in three steps. In the first step, we document three new facts about commonalities in failing banks in the United States from 1863 through 2023. First, failing banks see a rise in non-performing loans and deteriorating solvency several years before failure. Second, failing banks increasingly rely on expensive and risk-sensitive non-core funding in the run-up to failure. Third, failing banks undergo a boom-and-bust in assets in the decade before failure. Asset losses thus often follow a period of rapid loan growth. These patterns point to the central role of deteriorating fundamentals for bank failures.

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. Instead, if failures are the consequence of deteriorating fundamentals, then failures can in principle be predicted based on past fundamentals.

We find that measures of bank fundamentals strongly predict bank failures. The probability of failure increases in both observable measures of insolvency risk and funding vulnerabilities. Moreover, failure is best predicted by the combination of elevated insolvency risk and funding vulnerability. A bank in the top 5$^{\text{th}}$ percentile of both insolvency risk and funding vulnerability has a 10- to 20-fold higher probability of failure, relative to the average bank. Moreover, the conditional probability of bank failure is generally high, although it is sensitive to the period considered. For example, a bank in the top 5$^{\text{th}}$ percentile of both measures has a 42% probability of failure over the next three years during the Great Depression (1929-1934), 13% in a sample covering years before the founding of the Federal Reserve (1880-1904), and 26% in the modern sample (1959-2023).

To assess the extent of predictability more formally, we estimate simple regression models in which we predict whether a bank will fail based on measures capturing a bank's risk of becoming insolvent (such as bank capitalization, income, or non-performing loans) and being exposed to funding vulnerabilities (such as the reliance on non-core funding). 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, the AUC for predicting failure next year is between 82-89%. In the modern sample, after the introduction of deposit insurance, the predictability of bank failures is even higher, with an AUC between 90-95%. Notably, the predictability of failures is nearly as high in pseudo-out-of-sample forecasting exercises.

Theories of bank runs suggest that failures that are caused by depositor runs should only occur in banks experiencing large deposit outflows before failure. That is, a large decline in deposits is a necessary condition for a run to constitute the original cause of failure. Therefore, we exploit that our data allows us to measure the deposit outflows in failing banks to separately study the predictability of bank failures with large deposit outflows. Not surprisingly, deposit outflows immediately before failure were large before the introduction of deposit insurance, but small after the establishment of the FDIC. More surprisingly, however, we find that failures with large deposit outflows tend to be easier to predict as failures without deposit outflows. We find that the AUC for failures with deposit outflows is generally higher than the AUC for predicting failures without deposit outflows. Thus, even in absence of deposit insurance and a central bank and thus in settings in which purely self-fulfilling runs could be a plausible common cause of bank failures, we find that fundamentals almost always play a key role. The evidence strongly suggests that non-fundamental panic runs are not a common cause of bank failures.

Our evidence is also consistent with the Office of the Comptroller of the Currency bank examiners' classifications of of individual bank failures. Notwithstanding the large deposit outflows, from 1863 through the late 1920s, most bank failures were classified by the OCC as being caused by losses, fraud, or external shocks. Despite popular narratives, runs and liquidity issues account for less than 2% of failures classified by the OCC.

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 the distribution of 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 are 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.

Which theories are most consistent with the patterns we document? Our findings challenge the empirical relevance of the notion that non-fundamental, purely self-fulfilling panic runs cause otherwise healthy banks or banking systems to become distressed and fail (see, e.g., Diamond and Dybvig, 1983). More broadly, the importance of asset losses for failures goes against theories where bank failures and crises originate from shocks to the demand for liquidity (e.g., Allen and Gale, 2000). Our empirical approach does not allow us to identify whether a given bank failure with large deposit outflows was caused by a bank run or not.[2] However, we show that when runs on failing banks do occur, they only ever happen in banks with observable weak fundamentals. Our results are hence in line with the view that the causes of bank failures and banking crises are related to asset losses that lead to insolvency. To the extent that strategic complementarities matter for bank failures, they require weak fundamentals (see, e.g., Goldstein and Pauzner, 2005; He and Xiong, 2012). The central role of fundamentals in turn emphasizes the importance of *ex ante* interventions that increase the resilience of the financial system and reduce excessive risk-taking by banks.

Our findings also pose a challenge to theories of banking crises based on asymmetric information (see, e.g., Chari and Jagannathan, 1988; Gorton, 1988; Dang et al., 2017). Under this view, banking crises happen when depositors revise their assessment of a banks' risk of failure after receiving signals about the state of the banking system or the economy. These revisions, in turn, can induce system-wide runs by uninformed creditors that cause even healthy banks to fail. However, we find that weak banks that end up

[2] We also do not rule out that non-fundamental panic-based runs could lead healthy banks to suspend convertibility of deposits into cash. However, we argue such runs are not common cause of failures of otherwise healthy banks.

failing can be identified quite easily among their peers using publicly available financial statements, even years before their ultimate demise.

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

First, we relate to micro-level studies of bank failures and banking crises, such as empirical studies of the Great Depression (e.g., Calomiris and Mason, 1997, 2003; Mitchener and Richardson, 2019), the 2008 Global Financial Crisis (e.g., Gorton and Metrick, 2012; Krishnamurthy et al., 2014; Schmidt et al., 2016), the recent banking stress in March 2023 (e.g., Jiang et al., 2023), and other episodes featuring bank runs (Iyer and Puri, 2012; Frydman et al., 2015; Iyer et al., 2016; Artavanis et al., 2022).[3] The novelty of our approach is to bring together evidence from 160 years of micro-level data that spans a range of institutional and regulatory regimes. Thus, unlike existing research that uses micro-data to study bank failures and runs by narrowing in on specific episodes, our approach is to study the close-to-complete history of the banking system in the United States. This richness of the data allows us to document robust patterns in failing banks across various settings. For instance, we study bank failures in environments in which self-fulfilling runs are plausible but also settings in which they are explicitly addressed by government interventions. We provide several new findings to this literature, including the high predictability of bank failures, including those with runs, across the 160-year sample, the importance of the interaction of solvency and funding vulnerability for predicting failures, and the analysis of the OCC's classification of the causes of failure.

Second, our paper is related to studies of financial crises using aggregate data. Within this literature, our paper relates most closely to studies on the nature of banking crises

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

and the sources of bank failures and panics. Gorton (1988) and Calomiris and Gorton (1991) study banking panics in the National Banking Era and find that panics generally followed bad macroeconomic news but were not important for bank failures. Baron et al. (2021) argue that panic runs are not necessary for banking crises, and panics are preceded by bank equity declines, reflecting the realization of bank losses. Our paper provides complementary evidence by using granular bank-level data.[4] This allows us to show that deteriorating fundamentals are necessary for both individual and widespread bank failures, including failures with runs.

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

**Roadmap.** The paper proceeds as follows. Section 2 describes the data. Section 3 provides an overview of the evolution of bank failures and the regulatory framework for banks in the U.S. since 1863. Section 4 provides new facts about failing banks. Section 5 presents evidence on the predictability of bank failures. Section 6 studies bank failures

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

with and without runs. Section 7 shows that a measure of systematic risk from bank-level fundamentals predicts the major waves of banking failures in the U.S., and section 8 concludes.

# 2 Data

**Data for historical sample (1863-1941).** 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. 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. For most years, banks also report more granular items that allow us to measure non-performing loans and wholesale funding. However, the OCC did not require to report income statements. 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. We note that this definition of bank failure does not include banks that suspend convertibility of their debt into cash for a time and then reopen, as was common during banking panics of the National Banking Era. It also does not include banks that averted failure due to cooperation through, for example, bank clearinghouses. We emphasize this distinction, since the factors that lead to bank runs that are resolved by temporary suspension of convertibility may differ from those that lead to bank failures. The OCC collected detailed information on the post-mortem developments of failing banks. This information is also recorded in the OCC's annual report.[5] 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.[6] 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. Finally, until the late 1920s, the OCC classified bank failures by the cause of failure.

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 types of financial institutions that were not chartered under federal law but state law. National banks always coexisted alongside state banks, trusts, and private banks, with the relative importance of each type of institution varying over time. For example, national banks had a market share of the entire banking market ranging from around 80% in the 1870s to around 45% in the 1930s. See Figures A.1 and A.2 in the Appendix for details on the number and

[5]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.

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

market share of national banks, as well as White (1983).

**Data for modern sample (1959-2023).** For the modern, contemporary banking system we use the Federal Financial Institutions Examination Council (FFIEC) Consolidated Reports of Condition and Income ("Call Report"). These data provide quarterly information on balance sheets (FFIEC010) and income statements (FFFIEC013) on a consolidated basis for all commercial banks operating in the United States and regulated by the Federal Reserve System (FRS), the FDIC, and the OCC. Note that most existing research based on the Call Report 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. The FDIC defines a bank failure as the closing of a bank by a federal or state banking regulatory agency. The FDIC acts as receiver of the failed bank. 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.[7] Of these banks, 4,764 banks fail at some point throughout the sample period. Of these failing banks, 2,843 fail before 1935 and 1,921 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.

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

**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.

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

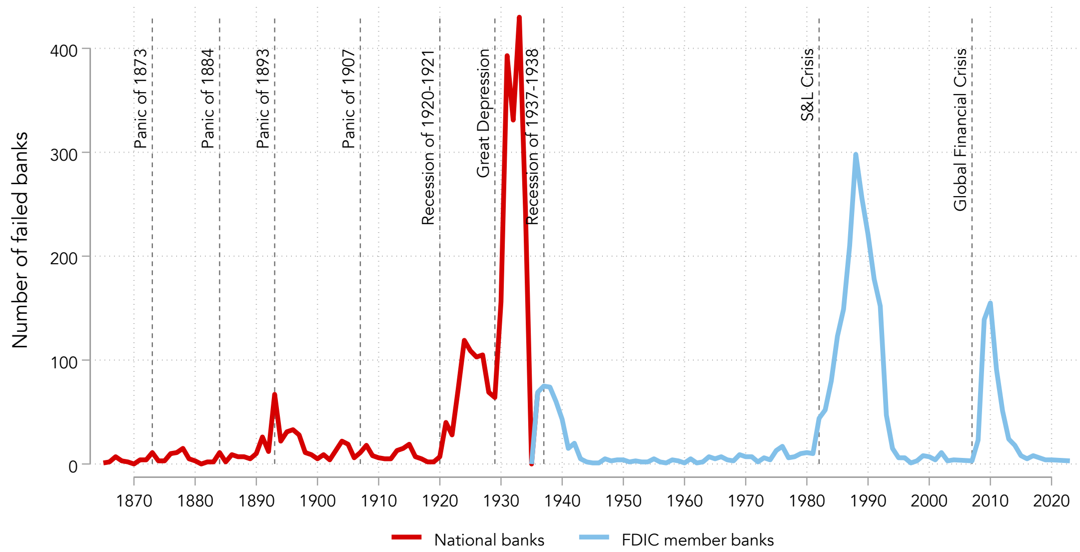
## 3 Evolution of the U.S. Banking System and Bank Failures

This section charts the evolution of bank failures and banking regulation in the U.S. since 1863. Figure 1 shows the number of failures and the failure rate throughout our sample. Table 1 summarizes the key institutional and regulatory features by era.

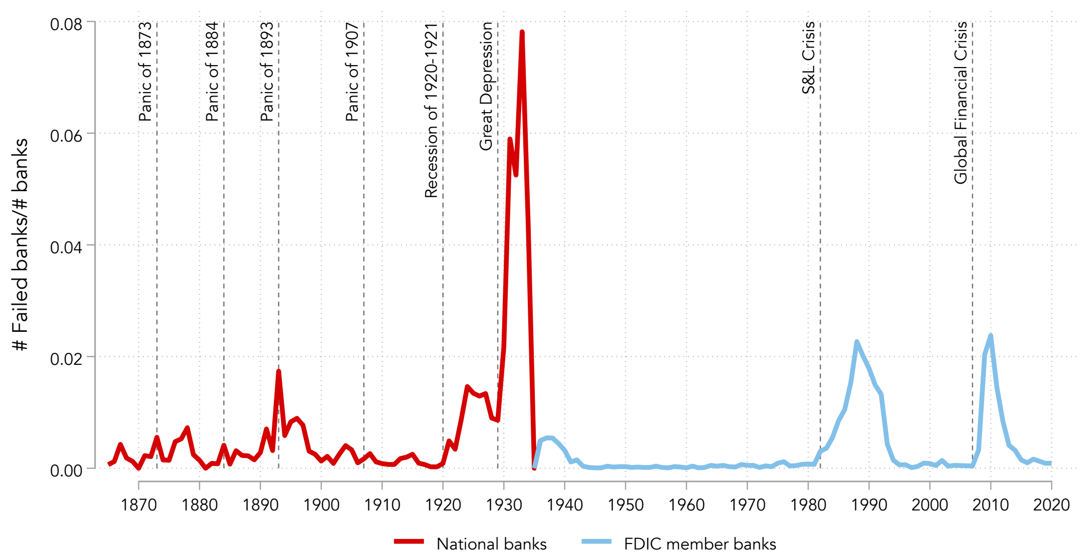
Our sample begins at the start of the National Banking Era, which spans the period between the Civil War and the founding of the Federal Reserve System, roughly 1863 to 1913. The National Banking Era emerged from reforms passed during the Civil War that allowed banks to be charted under federal law, 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

**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 and economic downturns. The red line plots the number/rate of failing national banks, defined as national banks placed into 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.

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 a central bank that could act as a lender of last resort.[8] Thus, in this period, we can be reasonably confident that bank and depositor behavior was not driven by the anticipation of government support. Capital regulation during the National Banking Era specified minimum dollar amounts of paid-in capital at the time of a bank's founding but did not restrict the leverage ratio (Carlson et al., 2022). Banks were able to choose their leverage freely subject to a restriction on dividend payouts 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. As a result, 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. Most of these "banking panics," however, were crises of limited liquidity. Except for the Panic of 1893, they were generally not associated with large increases in insolvency risk or bank failures (Calomiris and Gorton, 1991; Calomiris, 2000).[9] The banking panics of the National Banking Era highlighted the need for a lender of last resort, which ultimately led to the creation of the Federal Reserve in 1913. Thus after 1913, the US banking system had an active lender of last resort (Bernstein et al., 2010), although liquidity was not always provided during crises (Richardson and Troost, 2009).

The 1920s saw a rise in bank failures due to an agricultural depression and rising urbanization that weakened the position of rural banks (Friedman and Schwartz, 1963; Rajan and Ramcharan, 2015; Jaremski and Wheelock, 2020). Figure 1 shows that the failure rate of national banks climbed gradually in the 1920s. The Great Depression

[8] Clearinghouse associations operating at the city level provided emergency liquidity to member banks during panics (Gorton, 1985; Jaremski, 2018). Treasury performed quasi-central bank operations toward the end of the National Banking Era, but the interventions were small (Friedman and Schwartz, 1963).

[9] Calomiris and Gorton (1991) define banking panics as episodes when bank debt holders suddenly demand that a large fraction of the banking system convert debt claims into cash at par. They identified panics in 1873, 1884, 1890, 1893, and 1907.

further exacerbated distress among banks, and the rate of bank failures spiked to record highs in the early 1930s. The rise in failures during the Great Depression led to a wave of banking reforms. The most important of these was deposit insurance, introduced in 1933 and then made permanent in 1934 with the creation of the FDIC.

Bank failures were rare in the three decades after WWII, as banks' activities were restricted by the Depression-era regulations. The period of low bank failure rates came to an end in the second half of the 1970s. Bank failures further increased during the 1980s in the Savings and Loan Crisis. Failures in the 1980s were driven by a combination of high interest rates, severe recessions over 1980-1982, losses on oil and gas loans, and losses from exposure to the Latin American debt crisis.

Until the 1980s, there were no explicit capital ratio requirements. Instead, capital regulation was conducted by supervision. In response to rising failures and a trend of declining bank capital ratios, the 1980s saw the introduction of regulatory capital ratios. A simple leverage ratio requirement was introduced in 1985. The U.S. also implemented Basel I in 1991, introducing minimum capital requirements based on risk-weighted assets.

The last major wave of bank failures in our sample occurred in the 2008 Global Financial Crisis, following to collapse of the 2000s housing boom. The 2008 crisis led to a new wave of regulatory reform. Basel III and the Dodd-Frank Act imposed more stringent and more complicated capital requirements.

# 4 Three Facts About Failing Banks

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

## 4.1 Losses and solvency dynamics

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

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

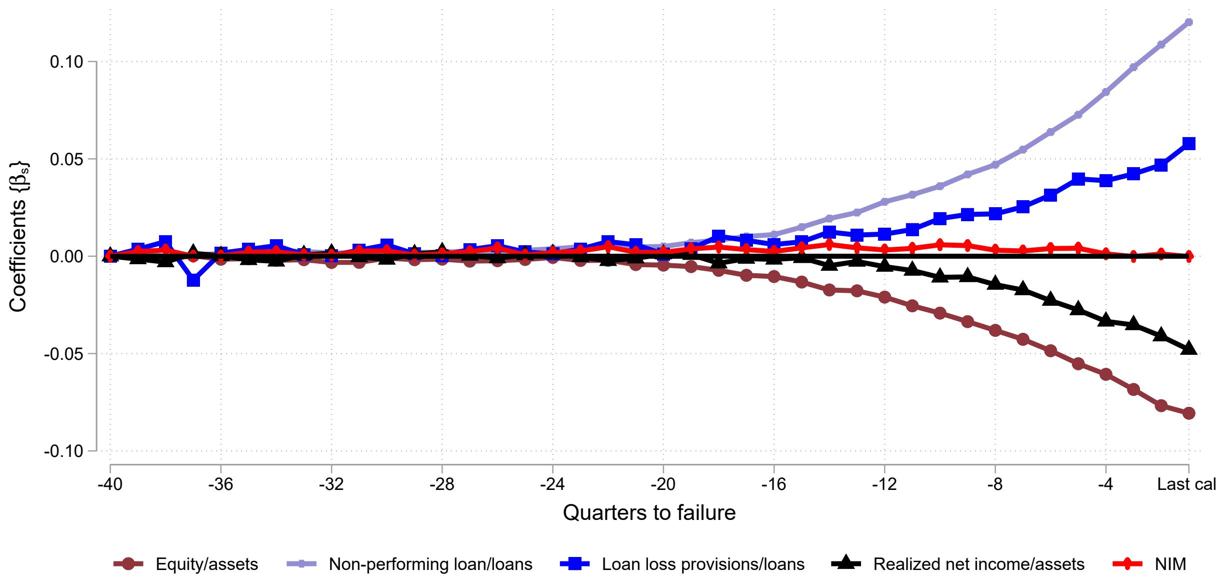
$$y_{b,t} = \alpha_b + \sum_{j=-10}^{0} \beta_j \times \mathbf{1}_{j=t} + \epsilon_{b,t}, \tag{1}$$

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

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

The patterns in Figure 2 suggest that failures are mainly associated with realized credit risk, rather than a deterioration in the net interest margin (NIM). The NIM is stable in the run-up to failure. In Appendix Figure A.4 we show that failing banks see both rising interest income (indicating higher risk taking) *and* rising interest expenses (in line with higher reliance on expensive forms of funding). Abstracting from valuation effects of holding long-dated fixed-rate securities, the resulting stable NIM suggests that the realization of interest rate risk is not a first-order source of failure for most failing banks. This is consistent with banks engaging in maturity transformation without taking on substantial interest rate risk due to the predominance of interest-insensitive deposit finance (Drechsler et al., 2021).[10]

**Figure 2:** ***Losses and Solvency of Failing Banks: 1959-2023***




Notes: The figure presents the sequence of coefficients from estimating Equation (1), where the dependent variable is the ratio indicated in the figure legend. The specification includes a set of bank fixed effects. The sample is restricted to failing banks, to the ten years before they fail, and to 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.

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 equity were not immediately impacted when

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

loans became non-performing. Nonetheless, the reported line items in national bank balance sheets allow us to construct proxies for non-performing loans and losses.

We use several approaches to proxy for non-performing loans and losses in the pre-1935 sample. First, we proxy for non-performing loans with the balance sheet item "Other Real Estate Owned" (OREO). This item reflects collateral seized and held on balance sheet, usually following foreclosure, and it is available for 1889-1904.[11] Second, fluctuations in bank profitability are reflected in the line item "undivided profits." This item represents funds that could be paid out as dividends to bank shareholders. Under capital regulation in the National Bank Act, banks would be likely to face restrictions on dividend payouts when undivided profits fell close to zero.[12] We therefore, 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. This measure is available from 1863-1904. Third, for the 1914-1935 period, we use the ratio of surplus profit to equity.[13]

Figure 3 illustrates the evolution of these proxies for losses for the 1863-1935 sample. In the decade before failure, failing banks see an increase in several measures 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 probability of a bank listing any non-performing loans rises by nearly 50 percentage points. Further, there is a 23-percentage point increase in the likelihood that a bank is restricted from paying out dividends because its undivided profit balance is too low. Panel (c) shows that banks failing between 1914 and 1935 saw

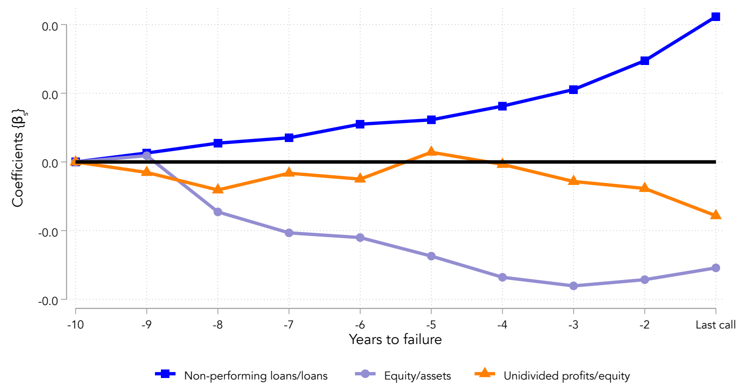
[11]OREO typically refers to real estate property assets that a bank holds, but that are not part of its business. Often, these assets are acquired due to foreclosure proceedings and are comparable to seized collateral. Note that OREO also pools collateral seized or acquired in foreclosure proceedings with other real estate the banks may have as part of relocation of banking premises. In Appendix Figure A.3, 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.

[12]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).

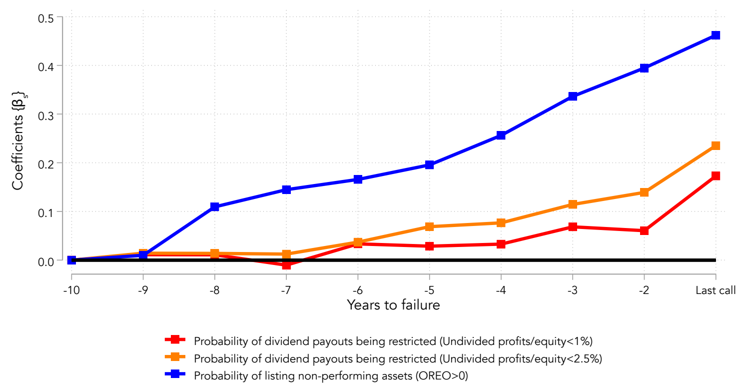
[13]The first two measures, OREO and undivided profits, are not broken out in the national bank balance sheets after 1904.

**Figure 3:** ***Losses and Solvency of Failing Banks: 1863-1935***

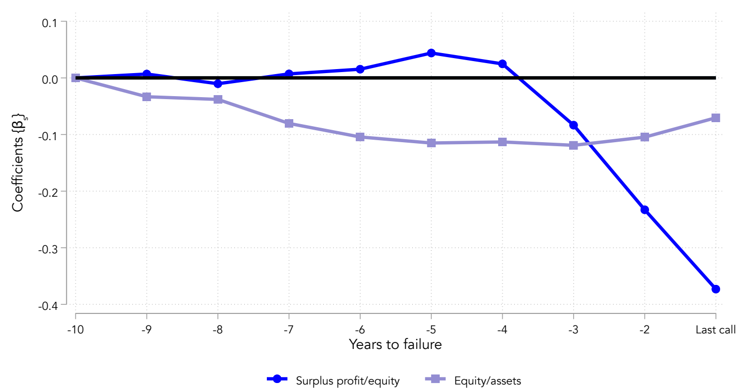
**(a)** *1863-1904: Equity and NPLs*




**(b)** *1863-1904: NPLs and Dividend Payout Restrictions*




**(c)** *1914-1935: Equity and Surplus Profit*




Notes: Each panel shows the sequence of coefficients from estimating Equation (1). The sample is restricted to failing banks and to the ten years before they fail. We proxy for non-performing loans with the line item "Other real estate owned (OREO)." Figure A.3 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. OREO is available for the 1889-1904 subsample. Restrictions on dividend payouts in panel (b) are proxied for by the share of undivided profits of total equity falling short of 1% or 2.5%. This measure is available for the period 1863-1904.

rapidly declining surplus profits relative to equity. Overall, for the pre-1935 sample, failing banks typically experienced rising losses several years before failure.

In line with losses on past investments playing a key role in failures, we also find that failing banks in the pre-1935 period had large asset losses. Table 2 provides statistics on the assets of failing banks at the time of suspension and the ultimate 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 represent another 36-50%. Therefore, bank examiners usually judged 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%.

The low recovery rate on assets does not allow us to draw definitive conclusions about the ultimate cause of failure. Asset values and recovery rates may in principle drop *because* the bank closed. This, in turn, allows for the possibility that runs that forced banks to close could have also reduced the value of the assets held. Thus, it is not straightforward to conclude that the low recovery rates necessarily reflect realized losses from poor fundamentals.[14] Nonetheless, it is telling 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 failure.[15] Consistent with this, Appendix Table A.4 shows

[14]Note, however, that the value of assets held at suspension cannot be reduced through a fire sale that occurred before failure. Rather, asset values implied by the recovery rate reflect the ultimate value after orderly liquidation during the bankruptcy proceedings, which allowed the receiver to hold the assets to maturity.

[15]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

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.[16]

**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 | 522 | 0.31 | 0.36 | 0.23 | 0.12 | 0.45 | 0.07 |
| Early Federal Reserve | 632 | 0.31 | 0.36 | 0.22 | 0.12 | 0.49 | 0.07 |
| Great Depression | 1677 | 0.33 | 0.50 | 0.12 | 0.08 | 0.40 | 0.04 |
| All | 2831 | 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.

## 4.2 Funding

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

How does bank funding evolve as a bank approaches failure? Figure 4 presents the evolution of various funding ratios in the decade preceding failure. Again, we present results separately for different time periods, as the the detail with which liabilities are reported changes over time. Panel (a) in Figure 4 shows results from estimating

losses, rather than liquidation discounts. Further, Granja et al. (2017) show that in the aftermath of the GFC, the average FDIC loss on a failed bank was around 28% of assets with a substantial part of these losses resulting from friction in the market for failed banks. Our evidence is broadly consistent with both James (1991) and Granja et al. (2017), although we find that the recovery rates were lower in the historical sample.

[16]The low recovery rates on assets in the pre-1935 sample meant that loss rates for depositors were substantial. Table A.5 in the Appendix 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. In the pre-FDIC sample, 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%.

Equation (1) using regular deposits, interbank deposits, and wholesale funding as the dependent variables for the sample of banks that failed before 1904. All variables are scaled by total assets. 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).

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 at a similar pace in percentage terms, but from a lower initial share of assets.[17] 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.

Panel (b) of Figure 4 presents the evolution of demand deposits and time deposits as a share of total deposits in the 1905-1928 sample. In this period, the national bank balance sheets 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.[18]

Panel (c) of Figure 4 presents the results for the post-1959 sample. For this sample,

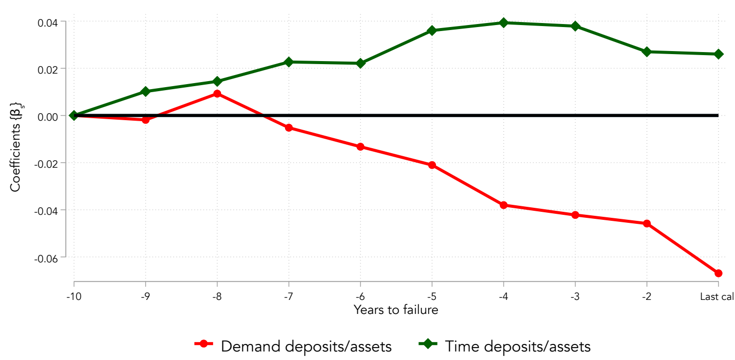
[17] Appendix Figure A.13 presents the dynamics of liabilities in logs, as opposed to as a share of assets.

[18] Figure A.12 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.

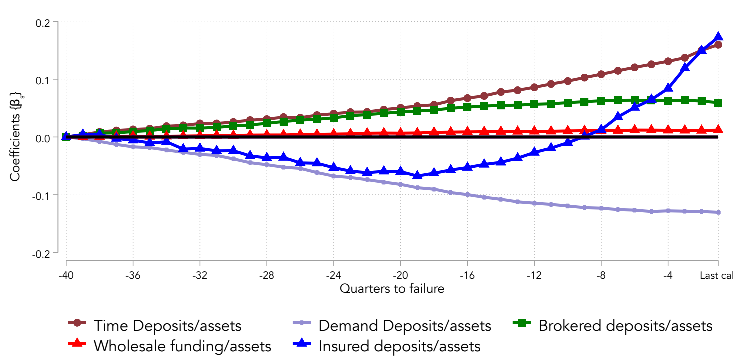
**Figure 4:** ***Funding of Failing Banks: 1863-2023***

**(a)** *1863-1904*


**(b)** *1905-1928*




**(c)** *1959-2023*




Notes: This figure shows 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.12 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 (c), 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.

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 increasingly rely on expensive types of deposit funding. In particular, the largest increase is accounted for by time deposits, followed by brokered deposits. Rates on both time deposits and brokered deposits exhibit a higher sensitivity to changes in the federal funds rate and are more sensitive to bank risk (see, e.g., Martin et al., 2023). As we show in the next subsection, these expensive sources of non-core funding are used to finance rapid growth. In contrast, demand deposits decline as a share of assets in the decade before failure. Demand deposits, unlike time or brokered deposits, tend to be held by less price-sensitive retail investors and tend to be a cheaper source of financing. Furthermore, while smaller in absolute terms, failing banks increasingly rely on wholesale funding. Wholesale funding also increases sharply right before failure (see Figure A.13 panel (b)). In contrast to the historical sample without deposit insurance, in the modern sample, insured deposits actually flow into failing banks. This suggests that insured depositors do not disciple failing banks, potentially delaying failure.[19]

## 4.3 Boom and Bust

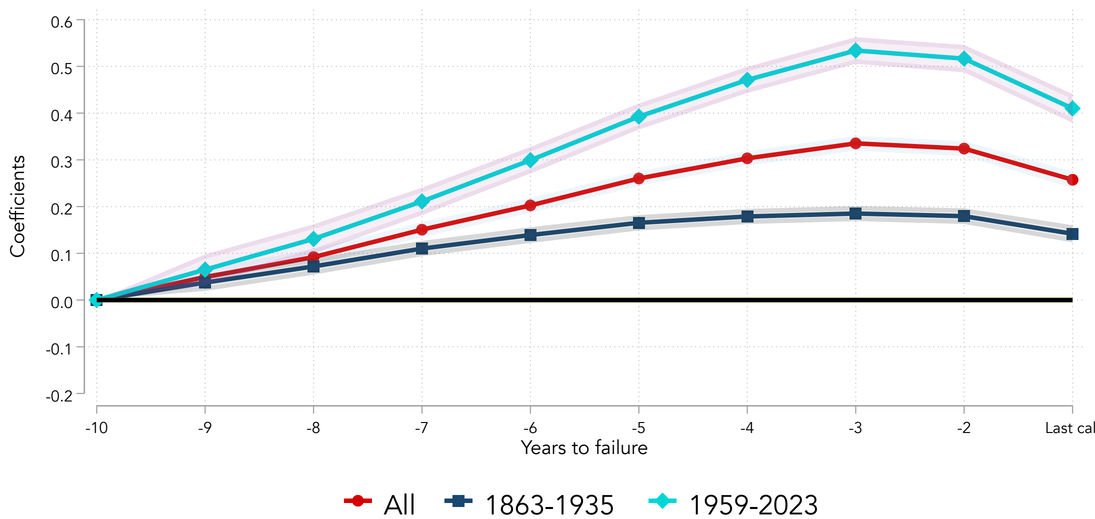
**Fact 3.** Failing banks follow a boom-bust pattern. They grow rapidly, both in absolute terms and relative to their peers, up to three years before they fail and then contract.

Why do banks experience gradually rising losses that eventually leads to failure? One hypothesis is that rapid loan growth leads banks to overextend themselves and incur

[19]These patterns are consistent with Martin et al. (2023), who find that failing banks increasingly substitute toward expensive deposit funding but also see an inflow of insured deposits before failure. The use of non-core funding to finance rapid growth is consistent with (Hahm et al., 2013). Rapid growth financed by brokered deposits before failure is also a feature emphasized in previous research surveyed by FDIC (2011). The FDIC restricts borrowing through brokered deposits for banks that are not well capitalized (i.e., for adequately and undercapitalized banks). Under the FDIC brokered deposit statute dating to 1989, undercapitalized banks may not accept brokered deposits (Section 29 of the Federal Deposit Insurance Act). Given an increased chance of enforcement actions in failing banks, see Figure A.5, growth of brokered deposits thus slows before failure.

future credit losses (Baron and Xiong, 2017; Fahlenbrach et al., 2018; Müller and Verner, 2023; Meiselman et al., 2023). Figure 5 presents results from estimating Equation (1) with the log of total assets as the dependent variable. The figure reveals that total assets in failing banks follow a boom-and-bust pattern in the decade before failure. In the full sample, assets expand by over 30% in real terms from ten years to three years before failure and then contract over the last two years before failure. Figure 5 also presents the dynamics of assets in failing banks separately for the pre-1935 sample and the modern sample. The boom-and-bust pattern is present in both samples. However, it is significantly more pronounced in the modern period.[20]

**Figure 5:** ***Assets in Failing Banks: 1863-2023***




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

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

[20] Figure A.6 shows the estimates across finer subsamples. Asset growth prior to failure is especially large in the period leading up to the 2008 Global Financial Crisis, followed by the 1959-1981 and 1982-2006 periods.

such as brokered deposits and funding in the Eurodollar market.[21] Third, in the historical period, national banks faced restrictions on lending against real estate, making them less exposed to real estate booms and busts, an important driver of large lending booms. Finally, the anticipation of government interventions and deposit insurance after the Great Depression may have increased risk-taking (Calomiris and Jaremski, 2019).

Which components of assets account for the overall boom in assets? Figure A.7 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. 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. For the modern sample, we can exploit the additional granularity of the data and decompose the expansion in lending by loan type. Figure A.8 shows that failing banks see the strongest boom in real estate lending (loans secured by real estate), followed by C&I lending. On the other hand, credit card and consumer lending are flat in real terms in the run-up to failure.

The boom-bust pattern is not simply driven by the fact that bank failures are more common at the end of a boom-bust cycle. First, the boom-bust pattern is similar for banks failing outside of major banking crises (see Figure A.9). Second, rapid asset growth predicts subsequent failure in the cross-section of banks (see Figure A.10).[22] In contrast, at short horizons, banks with lowest growth are most likely to fail.

[21] Accounts of major bank failures in the 1970s and 1980s begin to stress rapid growth financed by non-core funding as an important factor. For example, Franklin National Bank of New York and Continental Illinois were both the largest bank failures to date at the time of their failures. These banks both underwent rapid growth financed by wholesale funding, especially from the Eurodollar market (Federal Reserve History, 2023).

[22] The relation between asset growth and future failure is stronger in the 1959-2023 sample. For the historical sample, there is a strong relation between low growth and failure within one to three years, but a weaker relation between rapid growth and failure in five to six years (see Appendix Figure A.11).

# 5 Predicting Bank Failures with Fundamentals

Failing banks follow systematic patterns in terms of solvency, funding, and growth in the decade before failure. These banks experienced large asset losses, even in the before deposit insurance when failures could have been caused by non-fundamental runs. In this section, we study the extent to which these systematic patterns allow for the prediction of bank failures. Quantifying the predictability of bank failures based on bank fundamentals is important to establish that the patterns presented in Section 4 are not simply confounded by time trends. Moreover, the degree of predictability of bank failures also allows us to make inferences about the causes of failures that we can connect to theoretical models of bank failures.

On the one hand, if failures occur after 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).[23] On the other hand, if failures are driven by deteriorating fundamentals, or deteriorating fundamentals that cause creditors to coordinate on a run (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.

Under the first view, the inability of fundamentals to predict failure should especially apply to failures with large deposit outflows, since these are the failures where runs may have played a role. In the second view, fundamentals should be predictive of failure

[23]In principle, failures caused by non-fundamental panic runs due to "sunspots" could be consistent with any empirical pattern, since the theory does not discipline when sunspots occur (Gorton and Winton, 2003). However, our exercise is motivated by the idea that if bank failures are often caused by panic runs on healthy banks, as theories such as Diamond-Dybvig allow for, then these failures should not be predictable based on poor fundamentals.

even for failures with large deposit outflows, since deposit outflows occur in response to deteriorating fundamentals. Therefore, in addition to documenting the predictive content of fundamentals for predicting all bank failures, we separately study the predictability of bank failures with large deposit outflows, where failure likely involved a run by depositors.[24]

## 5.1 Insolvency, Funding Vulnerability, and Failure Rates

**Fundamentals and future failures.** We first provide a simple visualization of the future probability of failure as a function of bank fundamentals. In Figure 6, we plot the probability of failure over the next three years ($t + 1$ to $t + 3$) conditional on a bank's fundamentals in year $t$. We consider two measures of fundamentals. The first measure is a proxy for a bank's risk of insolvency. This measure is meant to capture a bank's distance to default. The second measure captures a bank's funding vulnerability. The second measure is meant to proxy for the cost and "flightiness" of the funding structure, such as the reliance on non-core funding. For example, wholesale funding is an expensive form of funding, especially for banks that are perceived as risky (Cooperman et al., 2023), and wholesale creditors are typically the most risk sensitive investors (see, e.g., Perignon et al., 2018; Blickle et al., 2022).

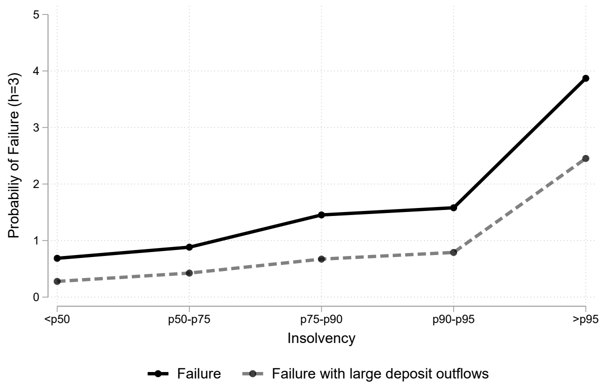
The exact variables we use to measure insolvency or funding vulnerabilities in Figure 6 differ across samples due to differences in data availability. For 1880-1935,[25] we measure insolvency by the reported undivided profits over equity. As discussed in Section 4.1, this measure is a good proxy for bank income and whether banks were restricted by low net income to pay out dividends. For the same period, we measure funding vulnerability by the share of wholesale funding over assets. As discussed above, this type of funding

[24] Note that while the OCC classified few failures are being *caused* by "runs," it is still be the case that many failures involve runs, given the pattern of large depositor outflows in Figure 8.

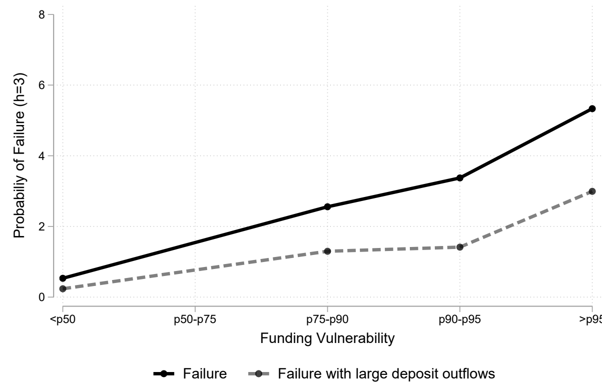
[25] We start in 1880 as we can only calculate deposit outflows before failure in failing banks from 1880 onwards.

**Figure 6:** ***Insolvency, Funding Vulnerability, and Future Probability of Failure***

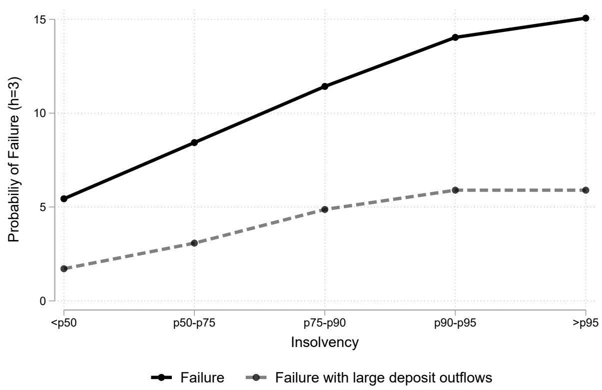
**(a)** *1880-1904: Insolvency*



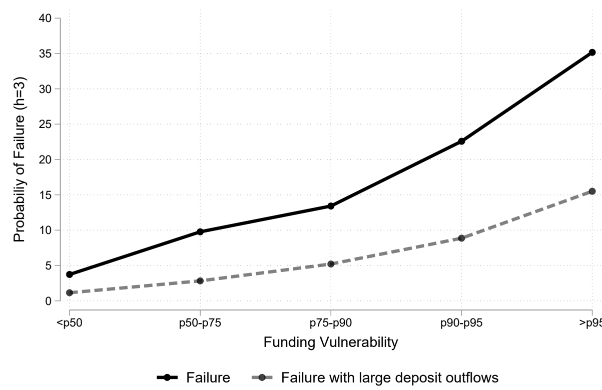

**(b)** *1880-1904: Funding Vulnerability*



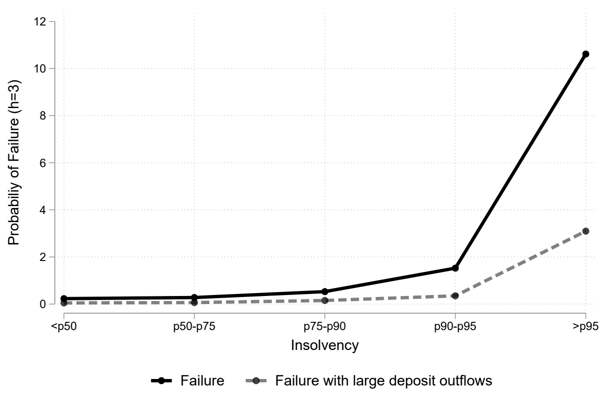

**(c)** *1929-1935: Insolvency*



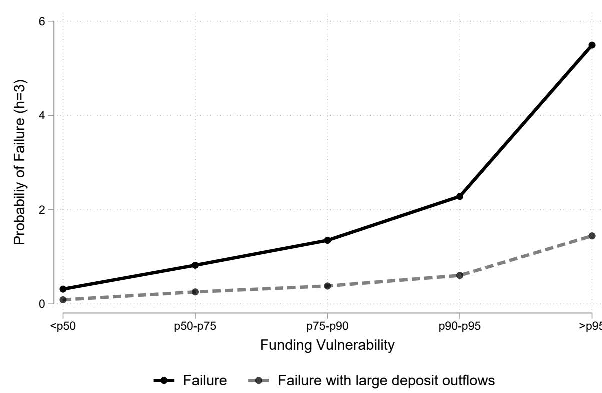

**(d)** *1929-1935: Funding Vulnerability*




**(e)** *1959-2023: Insolvency*




**(f)** *1959-2023: Funding Vulnerability*




Notes: This figure plots the probability of bank failure from $t + 1$ to $t + 3$ against the distribution of proxies for insolvency and funding vulnerability in year $t$. For the National Banking Era (1880-1904) and Great Depression (1929-1935), insolvency is measured by undivided profits over equity. As discussed in Section 4.1, this measure is a good proxy for bank income and whether bank were restricted by low net income to pay out dividends. Funding vulnerability is measured by wholesale funding over assets. For the Modern Era (1959-2023), solvency is measured by equity-to-assets, and funding vulnerability is measured by time deposits to total deposits. Failures with large deposit outflows are defined as those where deposits fall by more than 7.5% between the last call report and failure.

is a form of expensive interbank funding. For 1959-2023, solvency is measured by equity-to-assets, and funding vulnerability is measured by time deposits to total deposits.

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

Figure 6 plots the relation between the future probability of failure and measures of insolvency and funding vulnerability for the National Banking Era (1880-1904), Great Depression (1929-1935), and Modern Era (1959-2023). The probability of failure over the next three years is increasing in both exposure to insolvency and funding vulnerability. The relation is generally non-linear, with the risk of failure rising rapidly in the right tails. Moving from below the 50$^{\text{th}}$percentile to above the 95$^{\text{th}}$percentile in the measure of insolvency implies an increase in the probability of failure of 3.5pp in the National Banking Era, and 10pp in the Great Depression and the modern era. Funding vulnerability is even more predictive of failure in the pre-1935 data. Moving from below the 50$^{\text{th}}$percentile to above the 95$^{\text{th}}$percentile in funding vulnerability is associated with an increase in the probability of failure of 5pp in the National Banking Era, 30pp in the Great Depression, and 5.5pp in the modern era.

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

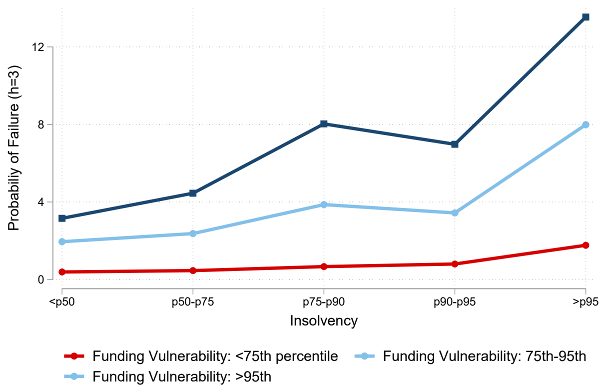
Figure 7 depicts the probability of bank failure over the next three years ($t+1$ to $t+3$) across the distribution of insolvency by whether funding vulnerability is below the 75$^{\text{th}}$ percentile, between the 75$^{\text{th}}$ and 95$^{\text{th}}$, and above the 95$^{\text{th}}$ percentile. Fundamentals are again measured in year $t$. The figure confirms that banks with both high insolvency risk *and* high funding vulnerability are the most likely to fail. The probability of failure for a bank that is in the top 5$^{\text{th}}$ percentile of both insolvency and high funding vulnerability is 13.0% in the National Banking Era, 42% in the Great Depression, and 26% in the modern era. These are large numbers, considering that the unconditional probability of failure over three years is only 0.8% in the National Banking Era, 4.2% in the Great Depression, and 1% in the modern era. Therefore, a bank with both high insolvency risk and high funding vulnerability has a 8-18 times larger probability of failure than a randomly drawn bank. Overall, this illustrates that fundamental measures of insolvency and fragile funding structure strongly predict future failure.

## 5.2 Performance of Fundamentals in Predicting Bank Failures

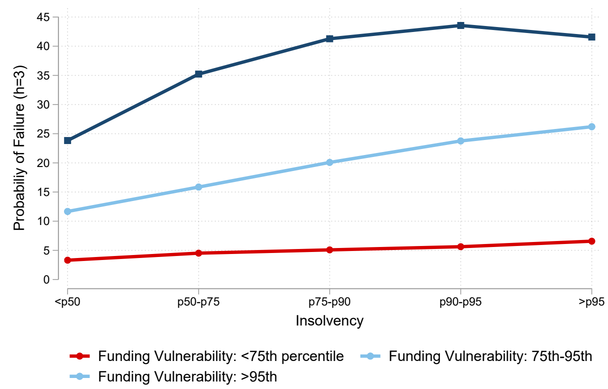
**Methodology.** Fundamentals are strongly associated with the future likelihood of failure. Can failures be predicted with a high degree of accuracy, that is, with a high true positive rate and a low false positive rate? We now conduct a formal prediction exercise to quantify the extent to which fundamentals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

**Figure 7:** ***Interaction of Insolvency and Funding Vulnerability for Predicting Future Bank Failures***

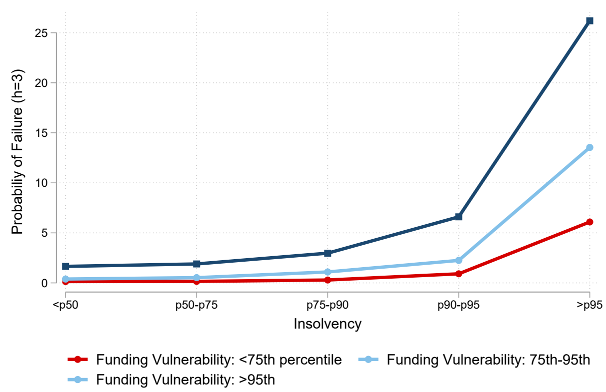
**(a)** *1863-1904*




**(b)** *1929-1935*




**(c)** *1959-2023*




Notes: This figure plots the probability of bank failure from $t+1$ to $t+3$ against the joint distribution of proxies for insolvency and funding vulnerability in year $t$. For the National Banking Era (1863-1904) and Great Depression (1929-1935), insolvency is measured by undivided profits over equity, and funding vulnerability is measured by wholesale funding over assets. For the Modern Era (1959-2023), solvency is measured by equity-to-assets, and funding vulnerability is measured by time deposits to total deposits.

We estimate simple predictive regression models of the following form:

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

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

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

Third, $\text{Growth}_{bt}$ is a set of variables that capture bank-specific growth. We use five quintiles of change in log bank assets from year $t-3$ to $t$. This allows us to capture the non-linear relation between past growth and failure (see Figure A.10). Fourth, for $\text{Aggregate Conditions}_t$, we include aggregate real GDP growth over the same three-year period. These latter two measures are available in the same form throughout the entire 1863-2023 sample. Note that we do not include bank or time fixed effects in the prediction; we only use real-time observables.

To quantify the power of these observables for predicting bank failure, we construct the receiver operating characteristic curve (ROC), a standard tool used to evaluate binary classification ability. The ROC curve traces out the true positive rate against the false positive rate as we vary the classification threshold. We then calculate the area under the ROC curve (AUC). An uninformative predictor has an AUC of 0.5, while an informative predictor has an AUC of greater than 0.5. The AUC metric is commonly used in the literature on predicting financial crises.[26] Furthermore, we test both in-sample

[26] 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).

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

**Main results.** Table 3 presents the in-sample and out-of-sample AUC statistics based on estimating variants of Equation (2). The table reports the predictive content of various sets of variables for the National Banking Era (1880-1904), Early Fed (1914-1928), Great Depression (1929-1935), and modern era (1959-2023). We present results for predicting failure at both the 1 year, 3 year, and 5 year horizons.

Bank failures are highly predictable based on the AUC metric. The in-sample AUC for the full specification in column (4) ranges from 82% in the Great Depression to 95% in the Modern Era. On their own, measures of insolvency and funding vulnerability both predict failures. The interaction between solvency and funding adds a significant additional boost to the predictive performance, especially in the National Bank Era, Early Fed Era, and the Great Depression. In the modern sample, where the predictability is extremely high, insolvency alone captures most of the predictive content of fundamentals.

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

The pseudo-out-of-sample performance is nearly as strong as the in-sample predictive performance. The exception is the Great Depression.[27] The high predictability also

[27] Changes in the data structure over 1914-1928 implies that we have a short training sample for the Great Depression pseudo-out-of-sample forecasting. We therefore train the model on the National Bank Era data

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

The high AUC statistics imply that bank failures can be classified with a high degree of accuracy. Figure A.15, Figure A.16, and Figure A.17 in the Appendix present a visualization of the ROC curve across models for the historical and modern samples. The ROC curve for the modern era implies that a forecaster willing to accept a 10% false positive rate can achieve a 85% true positive rate, again illustrating the strong predictability of bank failures.

**Additional Predictability Results.** The estimated coefficients for the prediction models reported in Table A.6, Table A.7, Table A.8, and Table A.9 reveal several other interesting results. Bank asset growth is significantly associated with failure. In the short-term, banks with low asset growth have the highest probability of failure. In contrast, at longer horizons of three to five years, the highest probability of failure is for banks that grow *quickly* from $t-3$ to $t$.[28] In 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.

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

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and use this to predict failures in the Great Depression.

[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.

**Table 3:** ***AUC Metric for Predicting Bank Failures with Fundamentals .***

| Prediction horizon $h$ | 1 year | | | | | 3 years | 5 years |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| **Panel A: National Banking Era (1880-1904)** | | | | | | | |
| AUC (in-sample) | 0.754 | 0.804 | 0.841 | 0.840 | 0.892 | 0.784 | 0.760 |
| AUC (out-of-sample) | 0.755 | 0.800 | 0.837 | 0.836 | 0.880 | 0.792 | 0.770 |
| N | 73389 | 73510 | 73389 | 73316 | 73316 | 73316 | 73316 |
| No of Banks | 5141 | 5148 | 5141 | 5137 | 5137 | 5137 | 5137 |
| Mean of dep. var. | .38 | .38 | .38 | .38 | .19 | 1.1 | 1.7 |
| **Panel B: Early Federal Reserve (1914-1928)** | | | | | | | |
| AUC (in-sample) | 0.826 | 0.627 | 0.852 | 0.888 | 0.902 | 0.818 | 0.765 |
| AUC (out-of-sample) | 0.830 | 0.601 | 0.800 | 0.806 | 0.790 | 0.763 | 0.747 |
| N | 69156 | 63137 | 62328 | 62214 | 62214 | 62214 | 62214 |
| No of Banks | 9151 | 9066 | 9055 | 9053 | 9053 | 9053 | 9053 |
| Mean of dep. var. | .53 | .56 | .55 | .55 | .34 | 2.2 | 4.6 |
| **Panel C: Great Depression (1929-1934)** | | | | | | | |
| AUC (in-sample) | 0.753 | 0.757 | 0.807 | 0.818 | 0.820 | 0.809 | 0.813 |
| AUC (out-of-sample) | 0.649 | 0.713 | 0.720 | 0.690 | 0.681 | 0.706 | 0.732 |
| N | 27749 | 27929 | 27697 | 27602 | 27602 | 27602 | 27602 |
| No of Banks | 7319 | 7322 | 7313 | 7304 | 7304 | 7304 | 7304 |
| Mean of dep. var. | 2.4 | 2.4 | 2.4 | 2.4 | 1.3 | 8.9 | 12 |
| **Panel D: Modern Era (1959-2023)** | | | | | | | |
| AUC (in-sample) | 0.944 | 0.807 | 0.949 | 0.951 | 0.948 | 0.878 | 0.815 |
| AUC (out-of-sample) | 0.931 | 0.783 | 0.938 | 0.938 | 0.936 | 0.854 | 0.787 |
| N | 616284 | 614914 | 614914 | 604967 | 604967 | 604967 | 604967 |
| No of Banks | 22102 | 22099 | 22099 | 22073 | 22073 | 22073 | 22073 |
| Mean of dep. var. | .27 | .27 | .27 | .27 | .054 | .88 | 1.4 |
| **Specification details** | | | | | | | |
| Insolvency | ✓ | | ✓ | ✓ | ✓ | ✓ | ✓ |
| Funding vulnerability | | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Insolvency × Funding vuln. | | | ✓ | ✓ | ✓ | ✓ | ✓ |
| Growth | | | | ✓ | ✓ | ✓ | ✓ |
| Withdrawals before failure | | | | | >7.5% | | |
| Age controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

Notes: This table reports the area under the receiver operating characteristic curve (AUC) across different specifications, samples, and horizons using in-sample and pseudo-out-of-sample classification. The corresponding regression coefficients underlying the models for Panel A can be found in Table A.6, Panel B in Table A.7, Panel C in Table A.8, and Panel D in Table A.9

# 6 Failures With and Without Large Deposit Outflows

We next exploit that our data allows us to calculate deposit outflows immediately before failure. These data allow us to ask: does the predictability of bank failures differ across failures that do and do not involve runs? A necessary, though not sufficient, condition for a depositor run to cause a bank failure is a large outflow of deposits. After all, theories of self-fulfilling bank runs typically require banks to engage in costly fire sales when subject to deposit outflows. Therefore, the sample of failures with large deposit outflows contains failures where the run itself can in principle have played a role in precipitating failure.[29]

A priori, bank failures with large deposit outflows could be either more or less predictable than other failures. Suppose large deposit outflows preceding failure are caused by factors unrelated to a bank's health. This could be driven by coordination failures that lead borrowers to run on a healthy bank (Diamond and Dybvig, 1983), a shock that increases cash demand but is uncorrelated with bank health (Chari and Jagannathan, 1988), or negative macroeconomic shock that leads uninformed depositors to run on all banks (Gorton, 1988). In this case, failures with large deposit outflows would be less predictable based on an individual bank's fundamentals. In contrast, suppose deposit outflows are driven by depositors learning bad news about bank fundamentals (Calomiris and Kahn, 1991; Allen and Gale, 1998; Goldstein and Pauzner, 2005). Then bad fundamentals should be predictive of these failures.

## 6.1 Deposit Outflows in Failing Banks

We first establish that deposit outflows before failure were large in the pre-1935 sample but small after the introduction of deposit insurance. Panel (a) of Figure 8 shows the relative difference between deposits reported in the last call report before failure and

[29]As additional robustness checks, we also study failures with large declines in asset holdings and find similar results to when conditioning on large deposit outflows. This addresses potential concerns of outflows in wholesale funding as opposed to deposit causing failure in runs.

deposits reported at the time of failure.[30] Deposit outflows were most pronounced during the National Banking Era and during the Great Depression, especially prior to the bank holiday in March 1933.[31] For example, for banks that failed during the Great Depression before the banking holiday, deposits declined by 13% between the last call and failure. In contrast, average outflows are much more modest after the introduction of deposit insurance.

Panel (b) of Figure 8 also shows that very large deposit outflows were not uncommon in the historical data. For instance, before 1933, around 25% of all failures featured deposit outflows exceeding 20%. We next exploit this additional information to study whether failures with deposit outflows are more or less likely in banks closer to insolvency and with higher funding vulnerability.

## 6.2 Predictability of Failures with Large Deposit Outflows

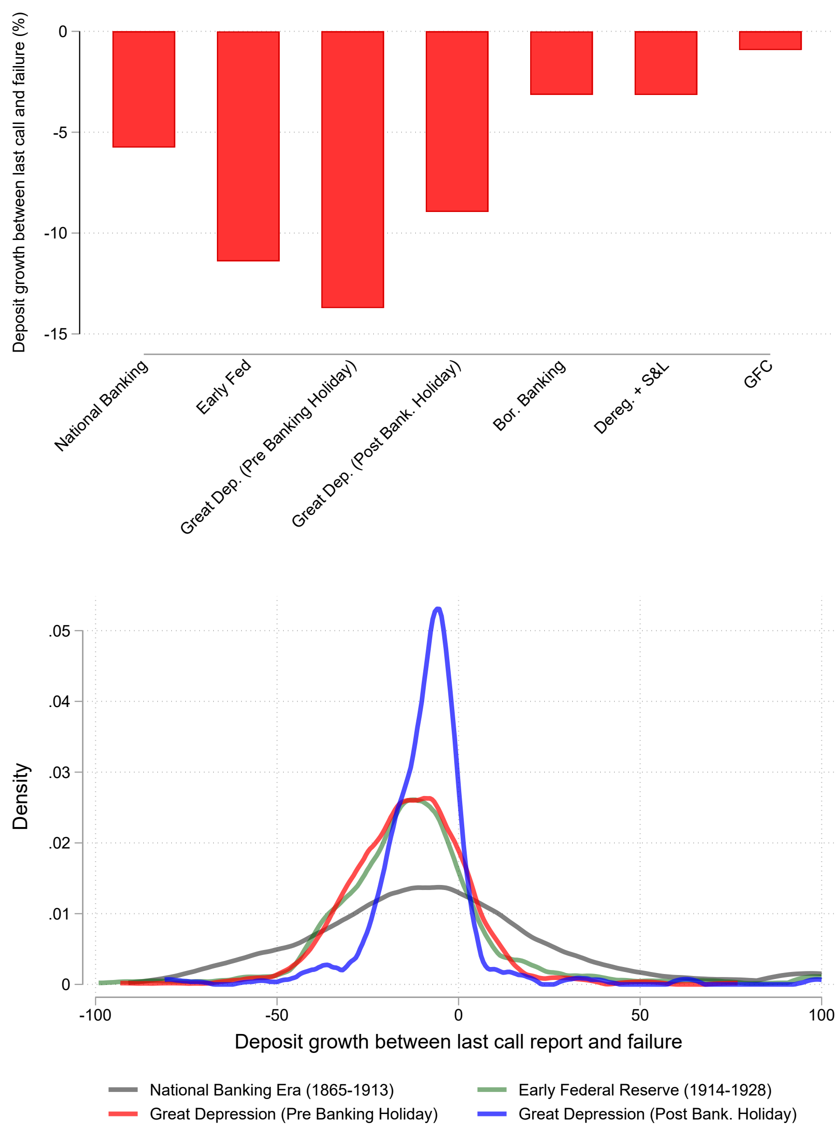
In Figure 6 above, in addition to plotting the conditional probability of failure for all failures, we also plot the probability of failures with large deposit outflows. We define a large deposit outflow occurring if deposits decline by more than 7.5% between the last call report and failure. The cutoff is necessarily arbitrary, but the results are robust to different choices of the cutoff.

Figure 6 reveals that fundamentals strongly predict failures with large deposit outflows. In both the National Banking Era and the Great Depression, moving from healthy fundamentals (below the 50$^{\text{th}}$percentile) to high insolvency or funding vulnerability is associated with an increase in the probability of failure that is similar to the increase for all

[30] For the historical sample, deposits at the time of failure are the deposits recorded at suspension by the OCC. For the modern sample, deposits at failure are based on deposits in the last financial statement from before failure reported to the FDIC. Typically, this last financial statement reflects more recent information than the last publicly available call report, but it may not necessarily reflect all outflows before failure. Figure A.14 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.

[31] For more details on the bank holiday in March 1933 see Jaremski et al. (2023).

**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.

failures. While failures with large deposit outflows are rare in the modern sample, these failures are also associated with significantly weaker fundamentals. Thus, the failures associated with large deposit outflows—failures that could have involved runs—were not wholly unexpected events that are disconnected from fundamentals. Instead, they are consistent with depositors reacting to weak bank fundamentals and anticipating failure.

Further, we estimate (2) separately for failures with large deposit outflows. Comparing columns (4) and (5) in Table 3 reveals that the predictive performance of fundamentals is at least as strong for bank failures with large deposit outflows before failure as for all failures. For example, in the National Banking Era, the in-sample AUC is 84% for all failures and 89% for failures with large deposit outflows. The in-sample AUC for the Great Depression is very similar for all failures and failures with large deposit outflows (82%). Failures with runs are thus easier to predict than runs without runs—possibly because the latter is more commonly related to fraud which in turn is less well detected in financial statements than realized asset losses from bad investments. This finding of high predictability of failures with deposit outflows clearly cuts against the view that failures before the Federal Reserve or deposit insurance were unpredictable and could occur in banks without weak fundamentals due to non-fundamental runs.

### 6.3 Additional Evidence: OCC Cause of Failure Classification

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

For most national bank failures occurring between 1863 and 1931, the OCC provides the "cause of failure" identified by the bank examiner. We classify the detailed causes of failure by the OCC into seven broad categories: excessive lending, losses, fraud, governance issues, run, external factors, and other factors (see Appendix Table B.2 for the exact classification). While it is possible that the OCC classification contains errors or biases, it nevertheless provides insight into what examiners on the ground saw as the main cause of failure.

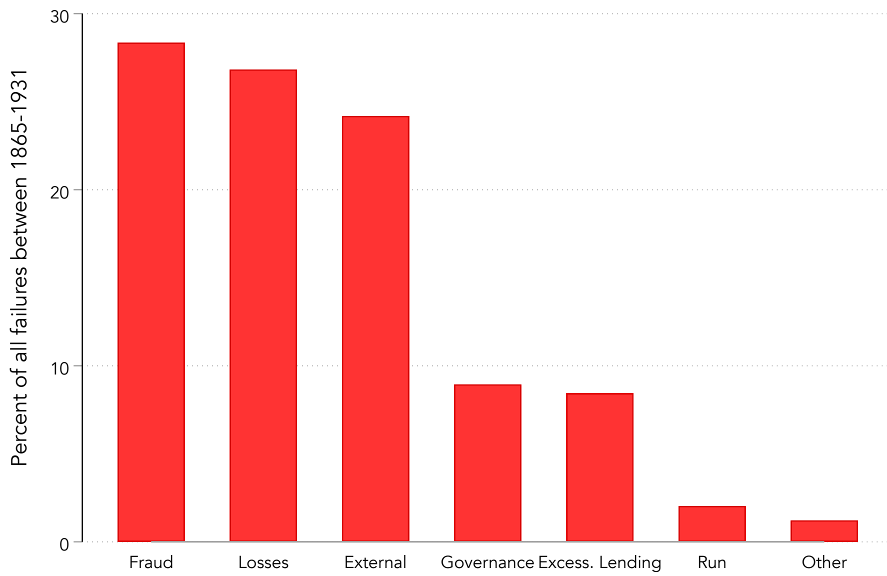
Figure 9 summarizes the distribution of the causes of failure for failures occurring between 1863 and 1931. Fraud and losses are the most common categories. This is followed by external shocks, a category that includes "deflation" and "crop loss." Other common causes are governance issues and excessive 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. The limited role for runs in explaining bank failures is also consistent with the low failure rates during most of the banking "panics" of the National Banking Era, since if runs were important for explaining bank failures, one would expect large spikes in failures in "panic" years.[32]

Systematic classification of the cause of bank failures by the OCC becomes sparse after 1928 and is not available for the period after 1931. Using classifications from the Federal Reserve Board of Governors, Richardson (2007) shows that, for the period 1929 through 1933, the main cause of failures (terminal suspensions) of Federal Reserve member banks was asset losses, though illiquidity from heavy withdrawals also played a contributing role. The evidence from the historical sample is also consistent with a detailed study conducted by the OCC of 171 bank failures between 1979 and 1987 (Graham and Horner,

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

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.[33]

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




Notes: Causes of failure are as classified by the OCC in in the tables of national banks in charge of receivers from the OCC annual report to Congress for various years. We categorize the detailed list of failure reasons as described in Appendix 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.

# 7 Fundamentals and Aggregate Waves of Bank Failures

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

[33]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."

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).[34]

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

Second, crises may feature *excess failures* beyond what is predicted by fundamentals during normal times due to amplification mechanisms. For example, crises can feature chain-reactions where bank failures lead to losses for other banks through interdependent claims (Allen and Gale, 2000; Acemoglu et al., 2015) and fire sales that weaken all banks (Gertler and Kiyotaki, 2015). 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

[34]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., 2017).

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 $\text{Insolvency}_{bt-1}$, $\text{FundingVulnerability}_{bt-1}$, their interaction, $\text{Growth}_{bt}$, and Aggregate $\text{Conditions}_t$. With this model estimated on data up until $t$, we predict the bank-specific failure rate in year $t+1$: $\hat{p}_{b,t+1|t}$ 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 $t$: $\{\hat{p}_{b,j|t}\}_{j=t_0:t}$.

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 $p_t^{cutoff}$:

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

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 90th percentile of distribution of $\{\hat{p}_{b,j|t}\}_{j=t_0:t}$. We refer to $BaR_t$ as *Banks-at-Risk*.[35] This measure captures the thickness of the right tail of the predicted failure distribution.[36] Second, we calculate the weighted average predicted failure rate

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

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

Figure 10 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.[37] We weight banks by

[35]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.

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

[37]In particular, we fit two models. The first model is for the expanding sample covering the 1863-1935

the log of assets to assign higher weight to larger banks. Results are similar without weighting.

Panel (a) of Figure 10 presents the results for the historical sample from 1863 to 1935. *Banks-at-Risk* forecasts the large rise in failures in the Panic of 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 10 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, Figure A.18 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 4 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

period. For this period, we use a model similar to column 4 Table A.6, 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 4 in Table A.9.

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.

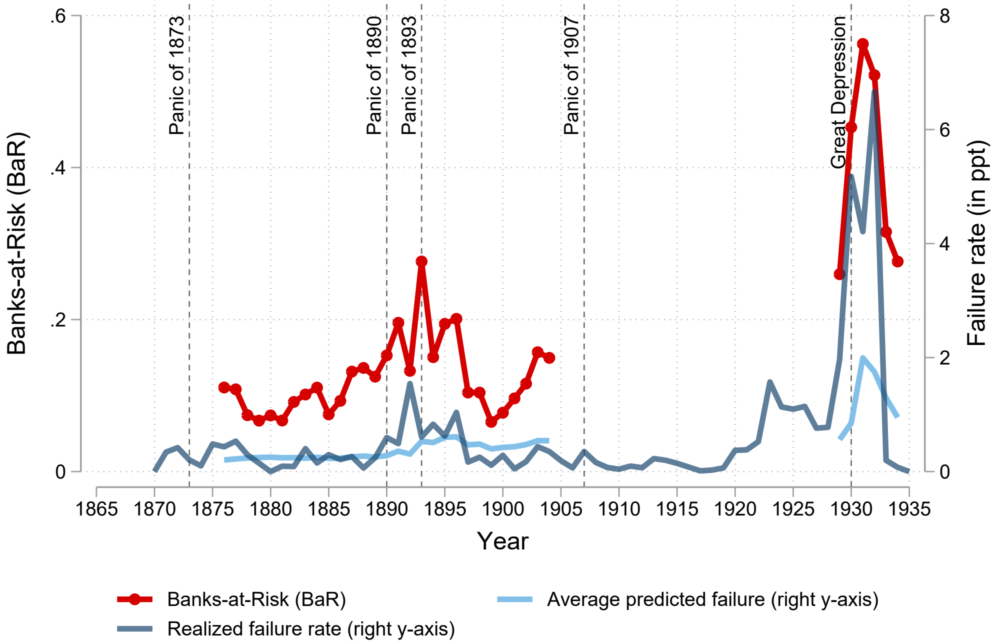
**Table 4:** ***Banks-at-Risk and Aggregate Bank Failures***.

| 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 |

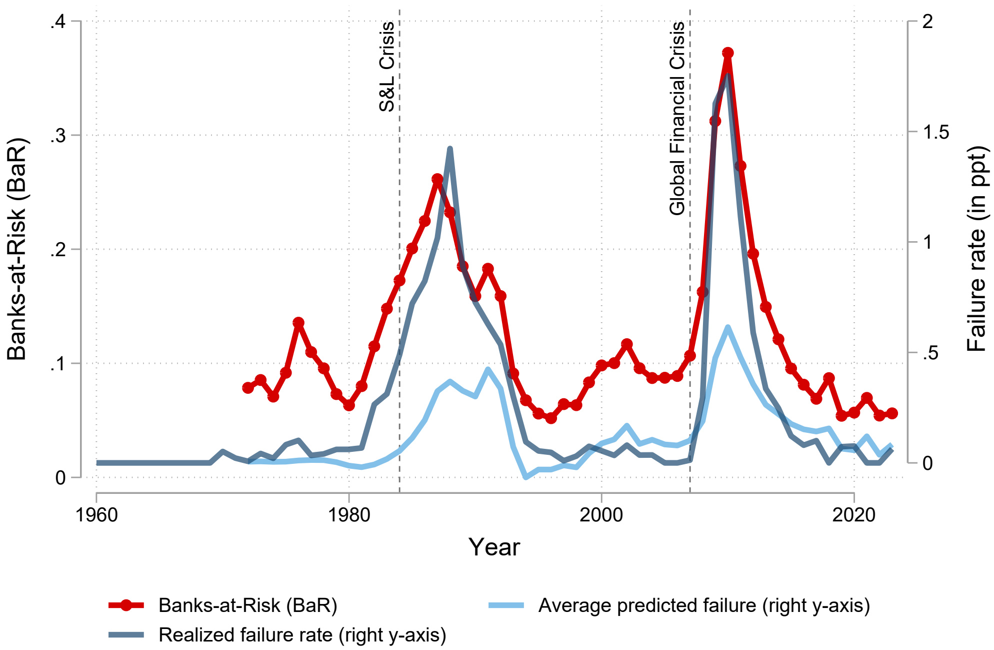
Notes: This table presents time series regression of the annual failure rate in year $t$ on Banks-at-Risk, $BaR_t$ or the average predicted failure rate $\overline{p}_t$. The measures on the right-hand-side are constructed on an expanding sample using only information up to $t-1$. Newey-West standard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

**Figure 10:** ***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.

# 8 Conclusion

This paper studies failing banks using data on more than 38,000 banks from the United States spanning 1863-2023. We characterize commonalities of failing banks over 160 years. The typical failing bank experiences rising losses and deteriorating solvency. At the same time, it increasingly finances itself with non-core funding. The most vulnerable banks are those with high losses *and* a high reliance on non-core funding. These robust observable patterns in failing banks, in turn, imply that individual bank failures and also aggregate waves of bank failures and banking crises are highly predictable. Altogether, the evidence suggests that the ultimate cause of bank failures is almost always and everywhere related to a deterioration of fundamentals.

We emphasize that our empirical approach does not allow us to identify whether self-fulfilling run dynamics are the cause of failures in those cases in which failing banks experience large deposit outflows. However, our evidence shows that runs which result in failure essentially never happen in absence of observable weak fundamentals. Moreover, we note that non-fundamental panic-based runs could force otherwise healthy banks or banking systems to suspend convertibility of deposits into cash. However, our paper clarifies that to the extent that such runs happen, they historically have not resulted in failures of healthy banks.

Despite the commonalities, some features of bank failures have also changed over the past 160 years. Before the advent of deposit insurance, failures involving large deposit outflows were common. This suggests that depositor runs could be important for determining the exact timing of failure. In contrast, in the modern era, deposit outflows are small, and insured deposits even flow into failing banks. This suggests important changes in the extent to which depositors discipline banks due to changes in regulation, as also argued by Martin et al. (2023). Moreover, lending booms preceding failure have increased over time, potentially consistent with increased risk-taking in response to the expanded safety net.

Our findings have at least two important implications. First, a large theoretical literature explores the role of panic-based runs in increasing financial fragility. There is comparatively less work to 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? Our evidence suggests that the deterioration of fundamentals is often linked to high growth in the past.

Second, the predictability of bank failures implies a role for *ex ante* interventions to prevent bank failures or mitigate their damage (Gennaioli and Shleifer, 2018). The fact that most bank failures can be identified supports the active use of prompt corrective action measures, such as limiting dividend payouts during and the use of non-core funding for poorly capitalized banks. More generally, our findings emphasize the importance of requiring financial intermediaries to be well-capitalized.

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# Failing Banks
## *Online Appendix*

Sergio Correia, Stephan Luck, and Emil Verner*

March 2, 2024

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

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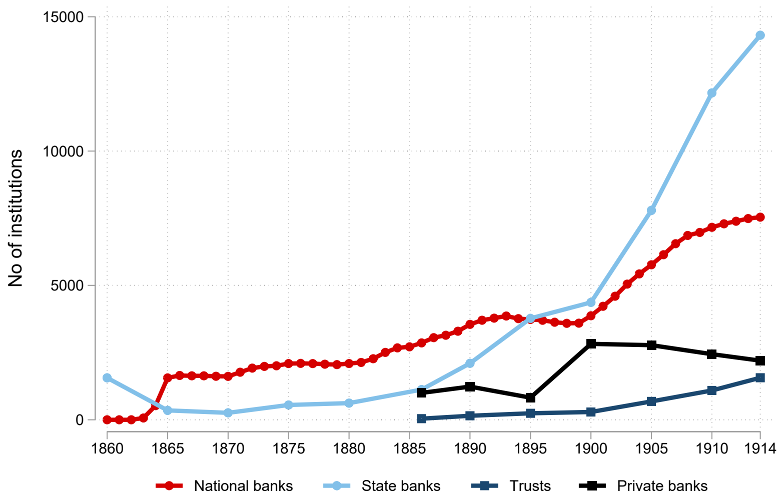
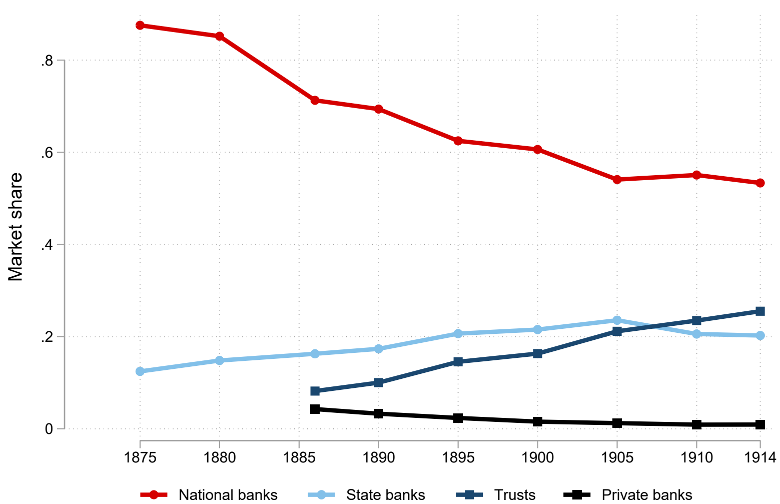
# A Appendix Figures and Tables

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

**(a)** *Number of banks*



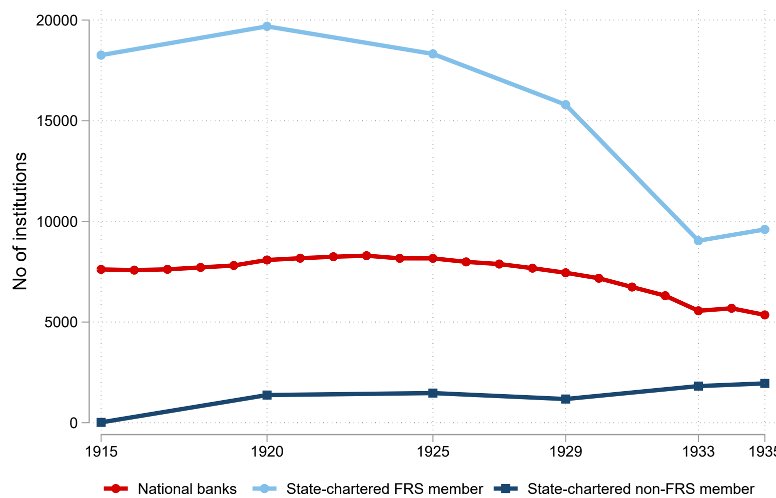

**(b)** *Market shares based on total assets*



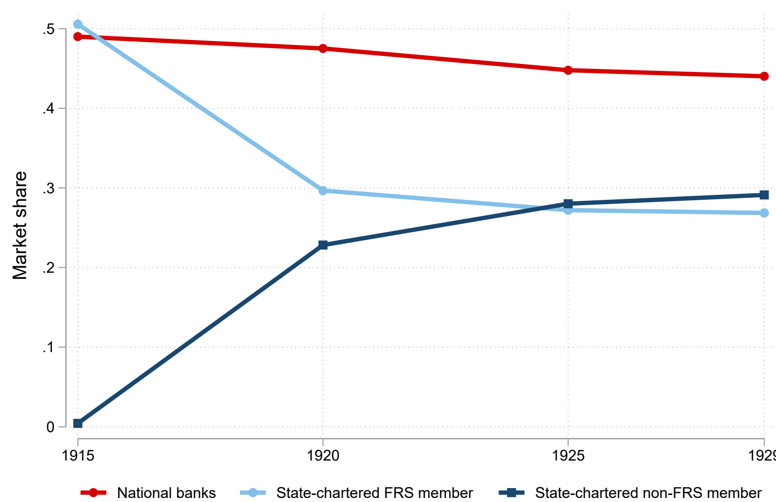

Notes: Data on state banks, trusts, and private bank are taken from White (1983). State bank assets are available from 1875 onwards; assets of trusts and private bank from 1886 onwards.

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

**(a)** *Number of banks*

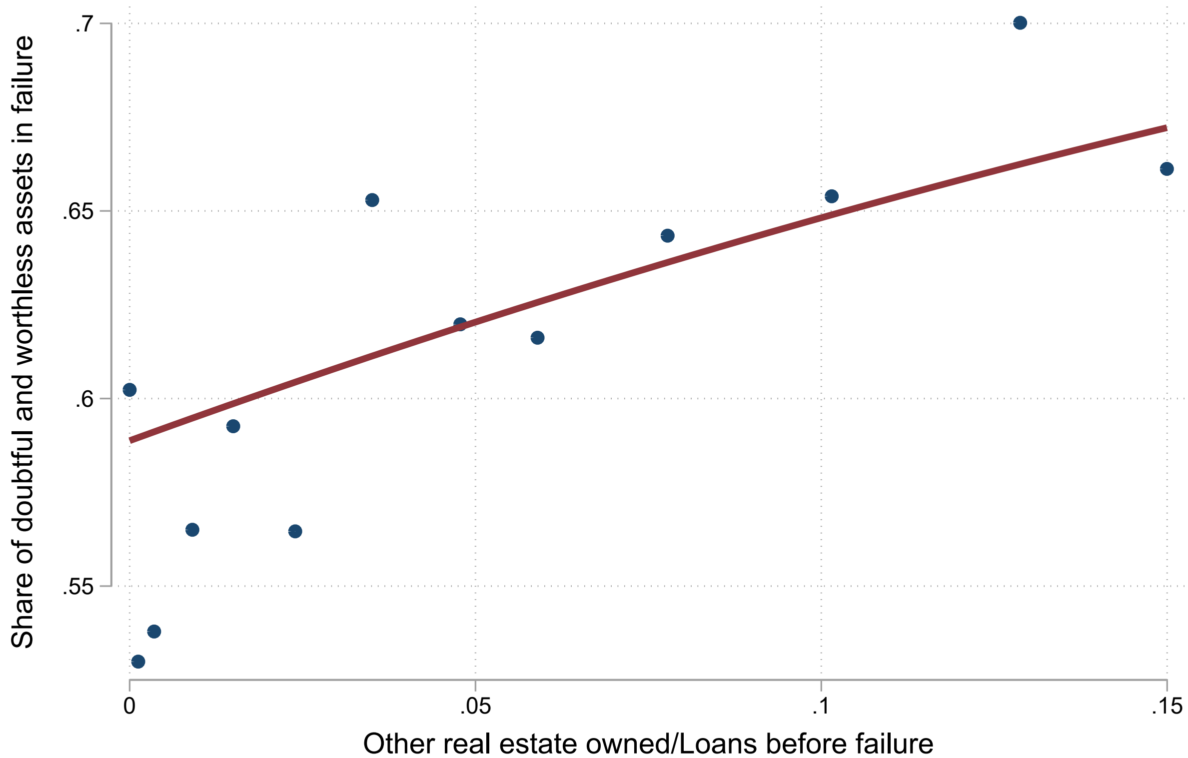



**(b)** *Market shares based on total deposits*



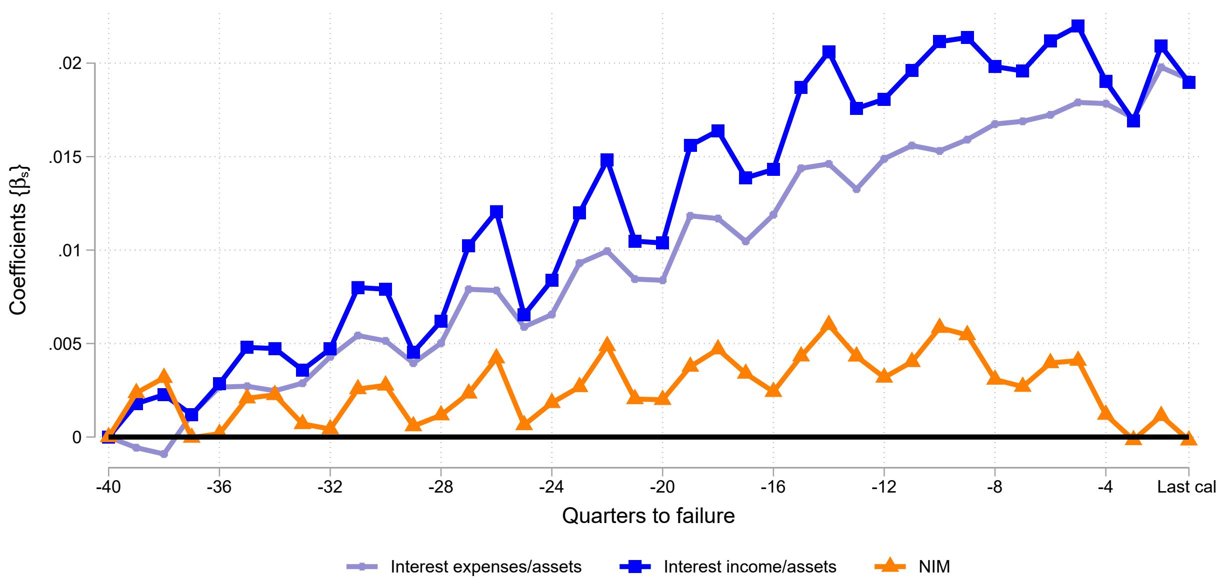

Notes: Data on both state-chartered member and non-member banks are taken from White (1983).

**Figure A.3:** ***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.4:** ***Interest Income, Expenses and NIM: 1959-2023***

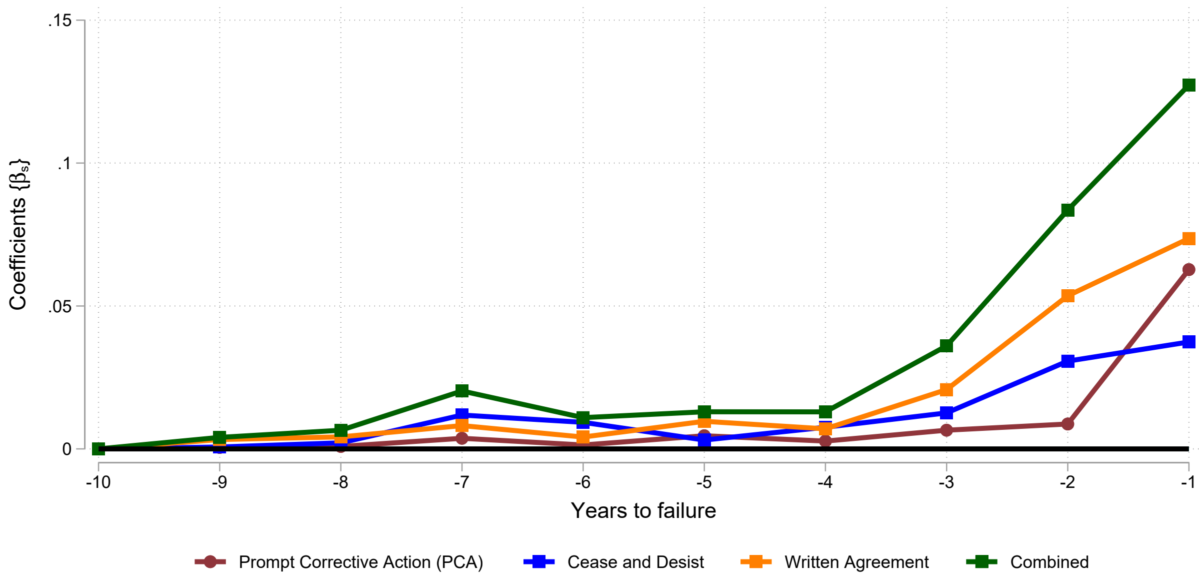



Notes: The figure shows the sequence of coefficients from a regression of the following form:

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

where $y_{bt}$ is the ratio indicated in the figure legends, and $\alpha_b$ 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.5:** ***Enforcement Action in Failing Banks: 1992-2023***

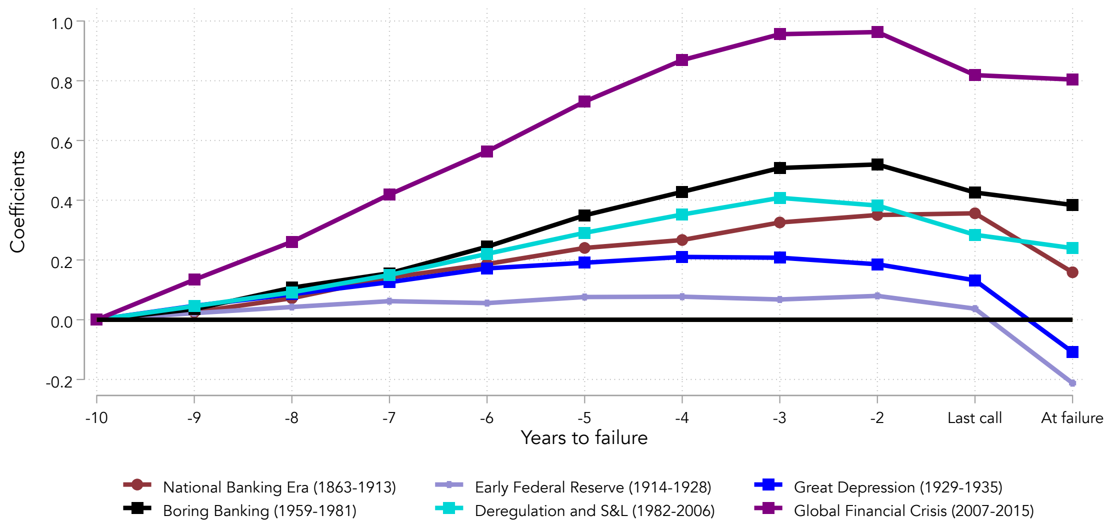



Notes: The figure shows the sequence of coefficients from a regression of the following form:

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

where $y_{bt}$ is a dummy indicating the enforcement action shown in the figure legends, and $\alpha_b$ 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 1992.

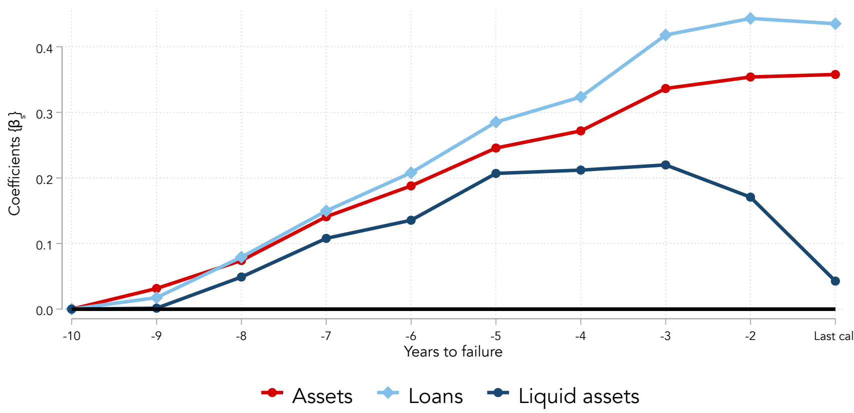
**Figure A.6:** ***Assets in Failing Banks: 1863-2023, By Historical Subsamples.***



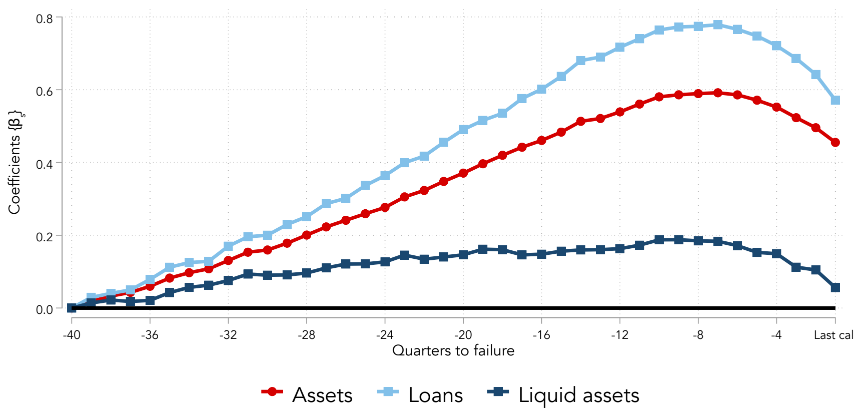

Notes: This figure reports the sequence of coefficients from estimating Equation (1) with log total assets (deflated by CPI) as the dependent variable for various subsamples. The regression includes a set of bank fixed effects. The sample is restricted to failing banks and to the ten years before they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

**Figure A.7:** ***Liquid and Illiquid Assets in Failing Banks***

**(a)** *1863-1935*

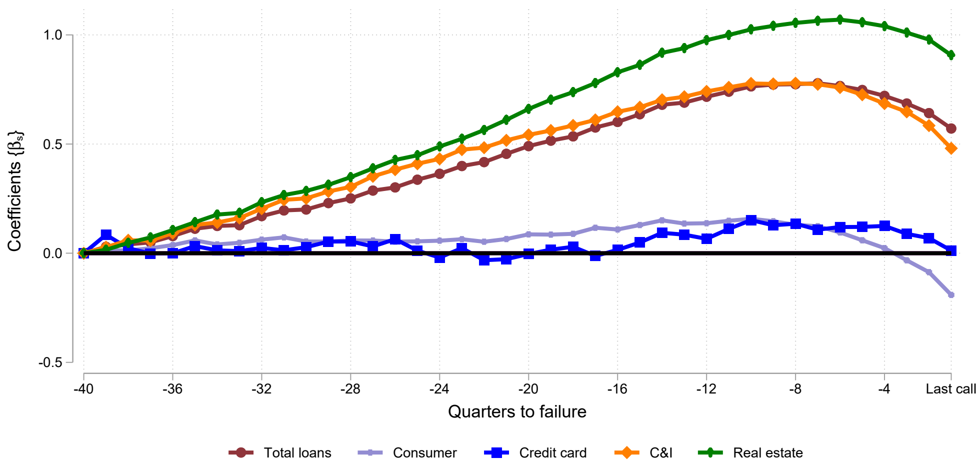



**(b)** *After 1959*




Notes: This figure plots the sequence of coefficients from estimating Equation (1) with the logarithm of either assets, loans, or liquid assets (all deflated by the CPI) as the dependent variable for different samples. The specification includes 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, bonds to secure deposits and bonds on hand, and 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 A.8:** ***Asset Growth in Failing Banks is Driven by Real Estate and C&I Lending.***

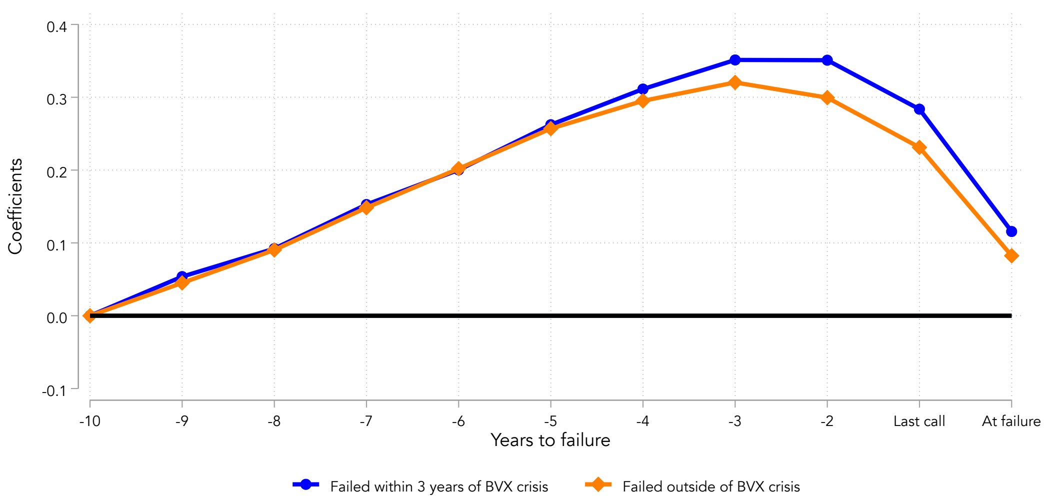



Notes: This figure presents the sequence of coefficients from a regression of the following form

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

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.9:** ***Asset Growth for Failures Occurring in Financial Crisis versus Normal Times.***

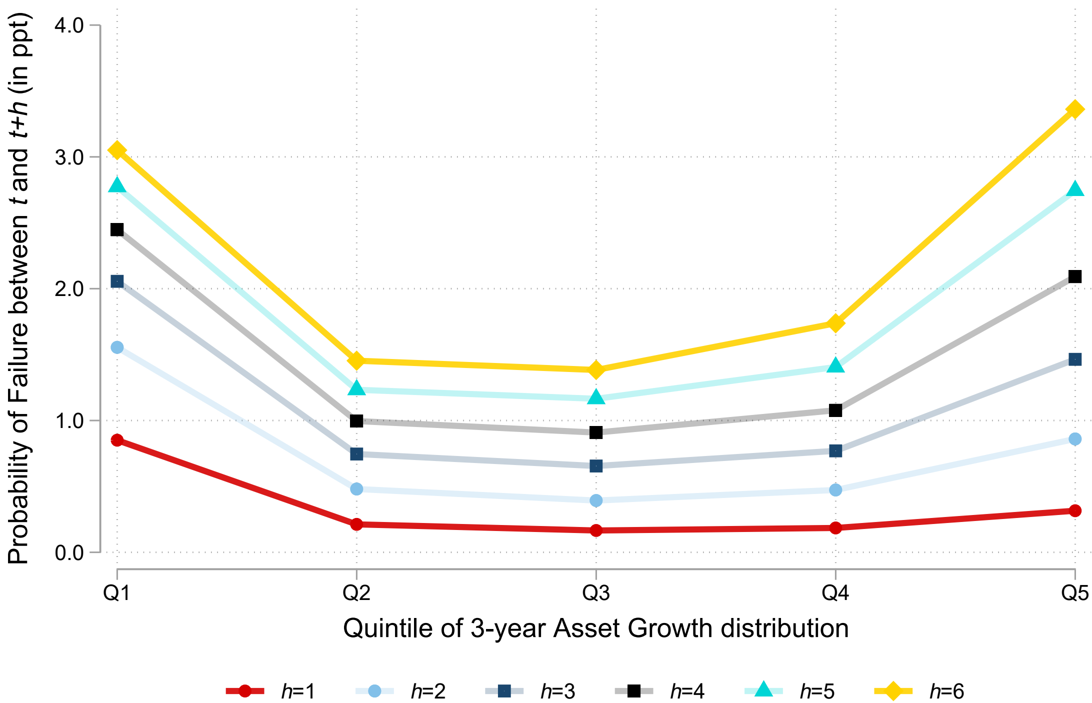



Notes: Both panels shows the sequence of coefficients from a regression of the following form:

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

where $y_{bt}$ is either bank $b'$ assets, deposits, or loans and $\alpha_b$ 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)

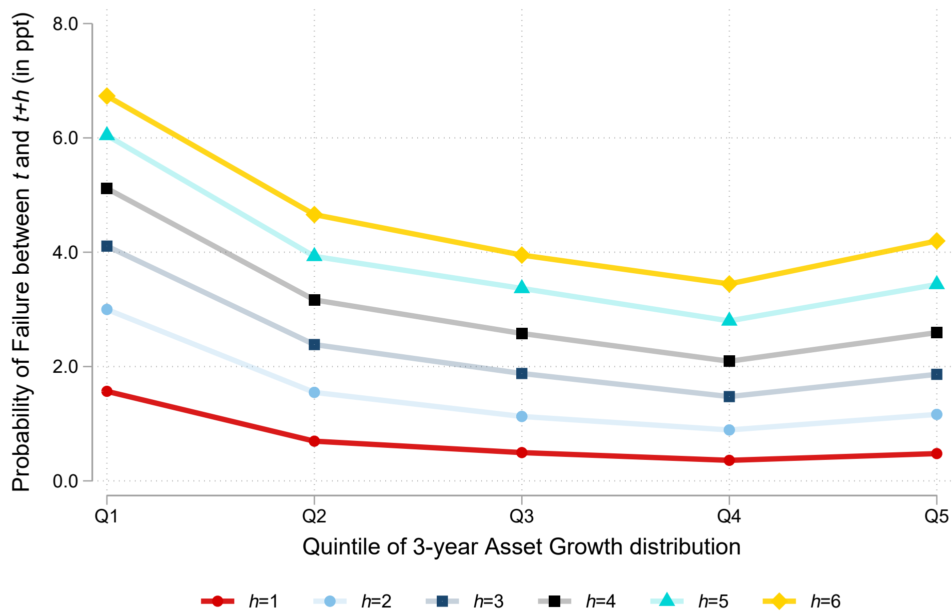
**Figure A.10:** ***Failure Probability in the Cross-Section of Asset Growth.***



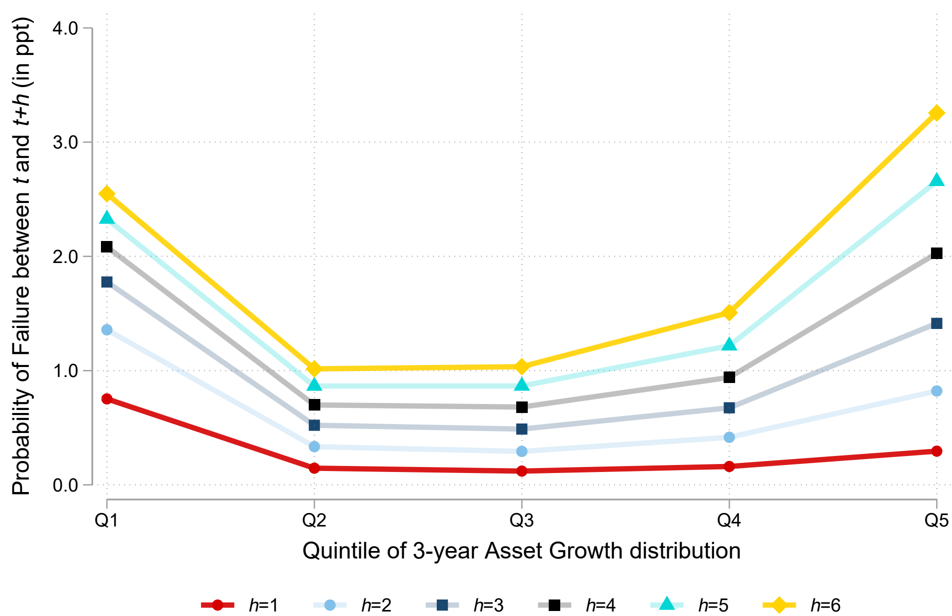

Notes: This figure plots the frequency of failure at the one to six year horizons across quintiles of the three-year asset growth distribution. Appendix Figure A.11 shows this figure separately for the pre- and post-FDIC samples.

**Figure A.11:** ***Non-Monotonic Intertemporal Relation between Growth and Failure Probability.***

**(a)** *Pre-1935*



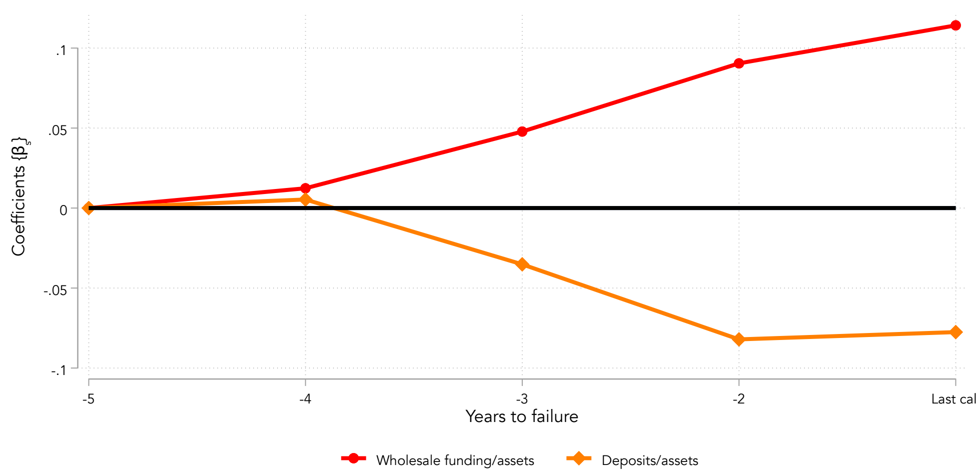

**(b)** *Post-1935.*




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.12:** ***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:

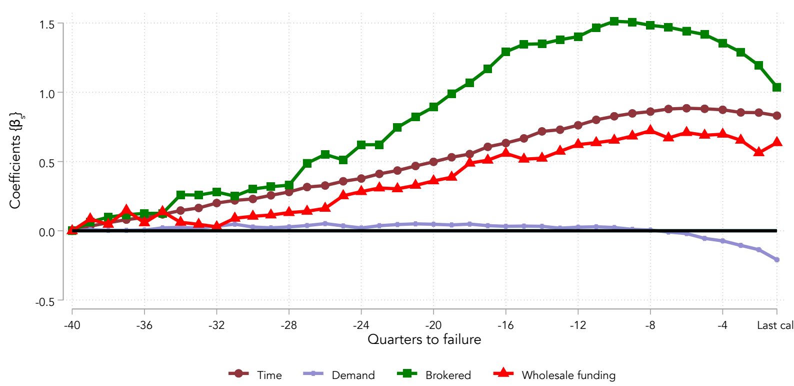
$$y_{b,t} = \alpha_b + \sum_{j=-10, j\neq -10}^{0} \beta_j \times \mathbf{1}_{j=t} + \epsilon_{b,t}$$

where $y_{bt}$ is the ratio indicated in the figure legends and $\alpha_b$ 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.13:** ***Funding of Failing Banks***

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


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

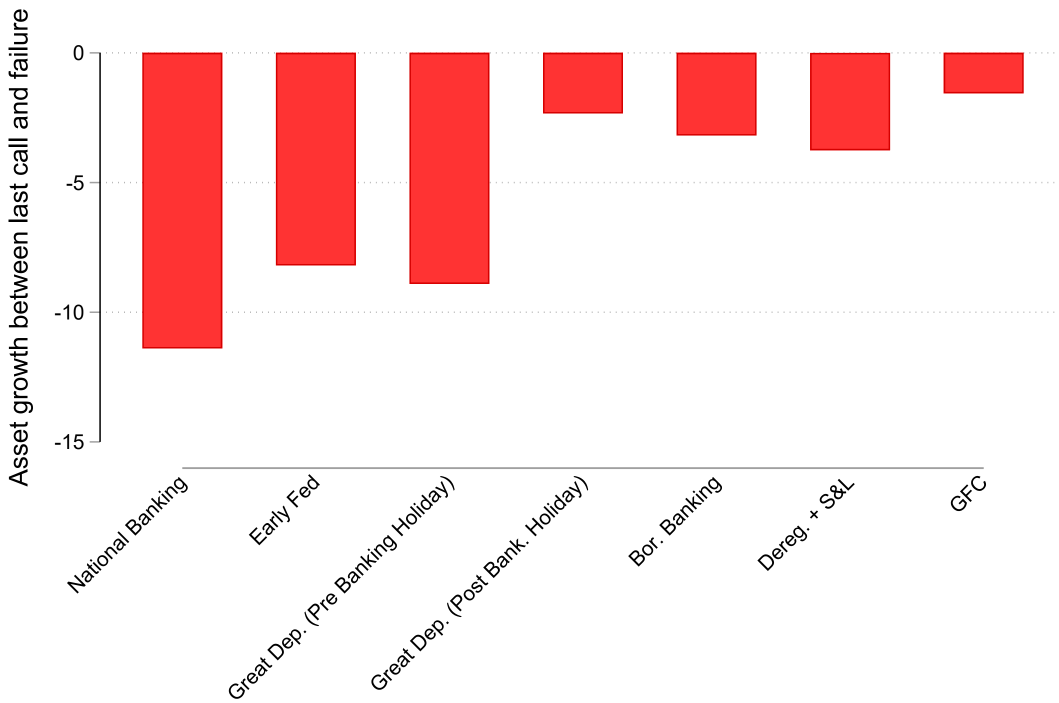



Notes: The figure shows the sequence of coefficients from a regression of the following form:

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

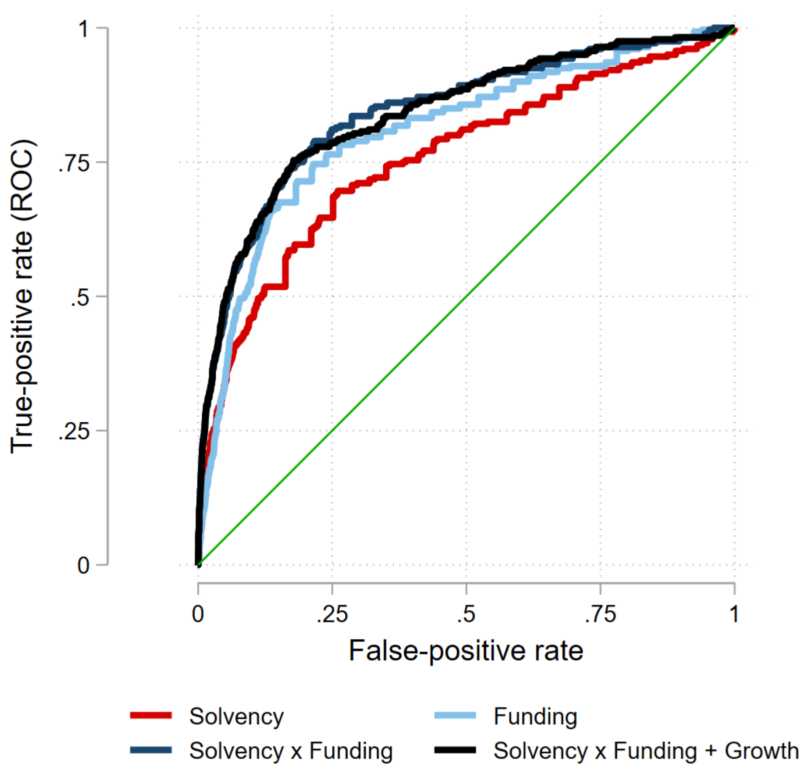
where $y_{bt}$ is the natural logarithm of the line item indicated in the figure legends and $\alpha_b$ is a set of bank fixed effects. The sample is restricted to failing banks and to the ten years before they fail. In panel (a), the sample is restricted to data from 1865 though 1904 and in panel (b) 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.14:** ***Asset Growth Between Last Call Report and Failure Date by Era***



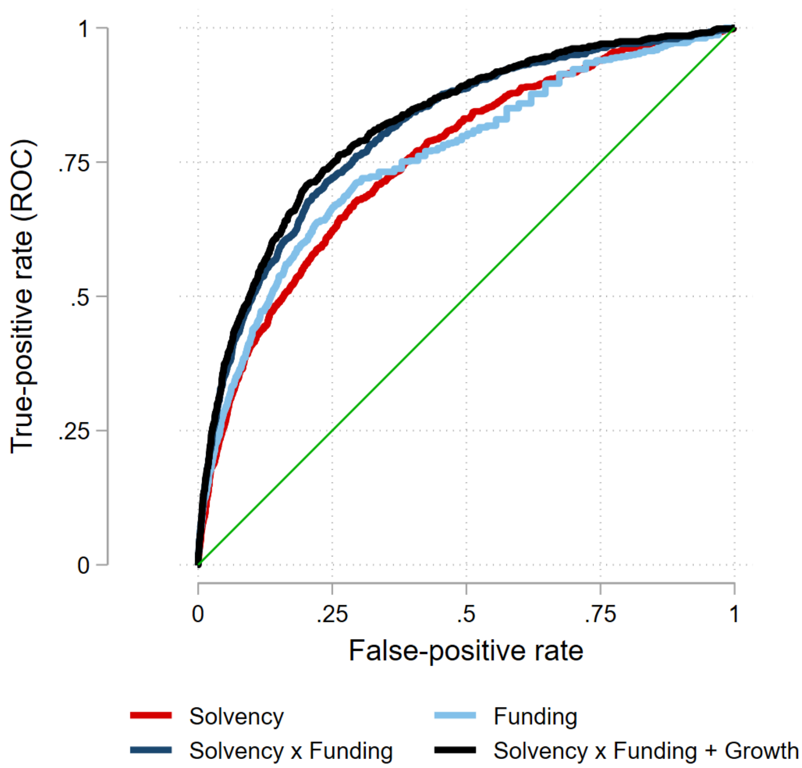

Notes: This figure reports the percent change between nominal asset holdings in the last call report before failure and the asset holdings reported in failure. Before 1935, assets in failure are as reported in the OCC annual reports table on national banks in receivership. After 1935, we use assets as 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.15:** ***ROC Curves: 1870-1904 Sample***



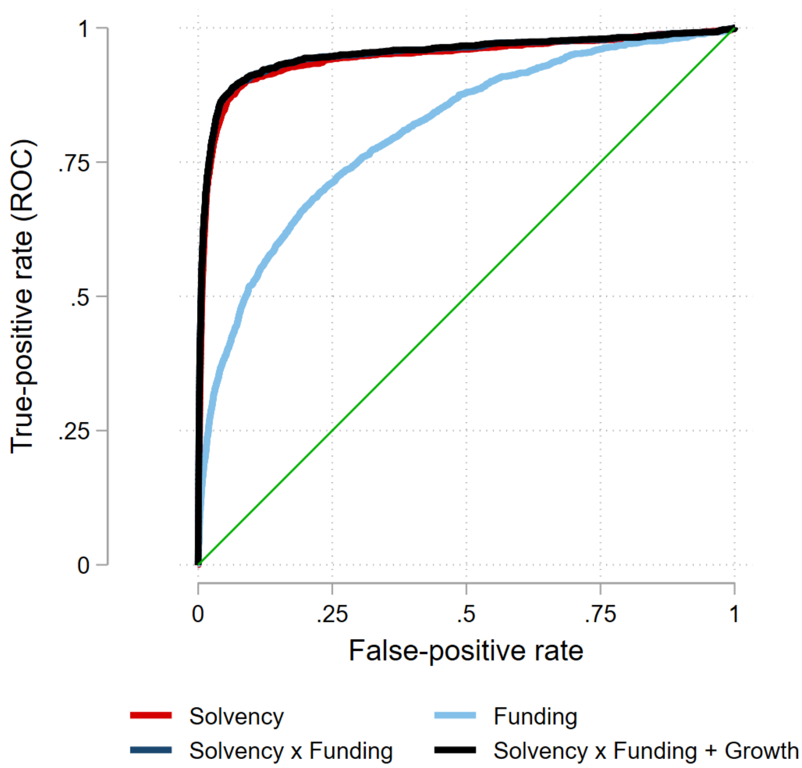

Notes: This figure plots the receiver operating characteristic (ROC) curve for the estimates based on columns (1) through (4) of Table A.6.

**Figure A.16:** ***ROC Curves: 1929-1935 Sample***



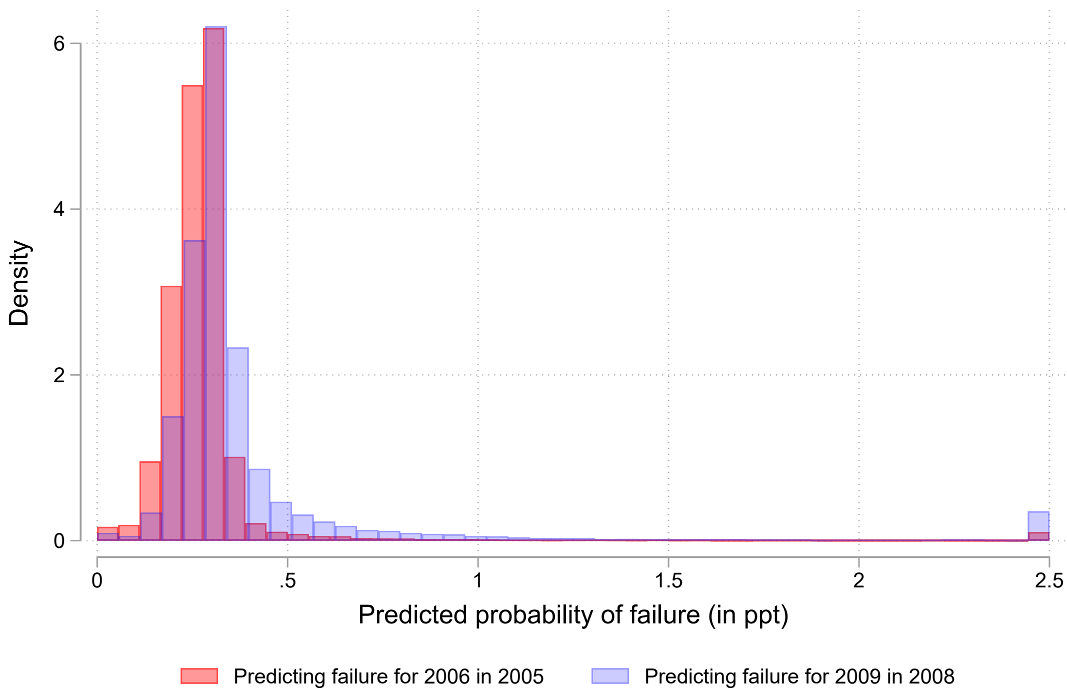

Notes: This figure plots the receiver operating characteristic (ROC) curve for the estimates based on columns (1) through (4) of Table A.8.

**Figure A.17:** ***ROC Curves: 1959-2023 Sample***




Notes: This figure plots the receiver operating characteristic (ROC) curve for the estimates based on columns (1) through (4) of Table A.9.

**Figure A.18:** ***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.

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

| | N | Mean | Std. dev. | 1st | 10th | 25th | 75th | 90th | 99th |
|---|---|---|---|---|---|---|---|---|---|
| Failing bank | 339,235 | 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 | 110,794 | 0.20 | 0.10 | 0.04 | 0.09 | 0.12 | 0.25 | 0.34 | 0.52 |
| NPL/loans | 57,539 | 0.02 | 0.04 | 0.00 | 0.00 | 0.00 | 0.01 | 0.05 | 0.18 |
| Wholesale funding/assets | 115,107 | 0.01 | 0.04 | 0.00 | 0.00 | 0.00 | 0.00 | 0.04 | 0.18 |
| Dividend payouts restricted | 115,248 | 0.05 | 0.21 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 1.00 |
| 3-year asset growth | 324,234 | 0.00 | 0.68 | -1.89 | -0.75 | -0.30 | 0.30 | 0.75 | 1.90 |

*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 | 2,479,699 | 0.06 | 0.24 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 1.00 |
| Equity/assets | 2,477,031 | 0.10 | 0.07 | 0.04 | 0.06 | 0.07 | 0.11 | 0.14 | 0.35 |
| Loans/assets | 2,477,031 | 0.55 | 0.16 | 0.11 | 0.34 | 0.45 | 0.66 | 0.75 | 0.88 |
| Deposits/assets | 2,479,660 | 0.86 | 0.10 | 0.44 | 0.79 | 0.85 | 0.91 | 0.92 | 0.94 |
| Liquid assets/assets | 2,476,607 | 0.37 | 0.16 | 0.05 | 0.16 | 0.25 | 0.47 | 0.58 | 0.78 |
| Loans/assets | 2,477,031 | 0.55 | 0.16 | 0.11 | 0.34 | 0.45 | 0.66 | 0.75 | 0.88 |
| Deposits/assets | 2,479,660 | 0.86 | 0.10 | 0.44 | 0.79 | 0.85 | 0.91 | 0.92 | 0.94 |
| Liquid assets/assets | 2,476,607 | 0.37 | 0.16 | 0.05 | 0.16 | 0.25 | 0.47 | 0.58 | 0.78 |
| Time deposits/assets | 2,436,526 | 0.36 | 0.16 | 0.00 | 0.12 | 0.25 | 0.48 | 0.55 | 0.67 |
| Wholesale funding/assets | 2,477,030 | 0.01 | 0.04 | 0.00 | 0.00 | 0.00 | 0.00 | 0.04 | 0.18 |
| Brokered deposits/assets | 1,461,792 | 0.01 | 0.08 | 0.00 | 0.00 | 0.00 | 0.00 | 0.03 | 0.22 |
| Net income/assets | 1,910,888 | 0.01 | 0.01 | -0.03 | 0.00 | 0.00 | 0.01 | 0.01 | 0.02 |
| NPL/loans | 1,354,307 | 0.02 | 0.03 | 0.00 | 0.00 | 0.00 | 0.02 | 0.04 | 0.12 |
| LLP/loans | 1,787,888 | 0.00 | 0.52 | -0.00 | 0.00 | 0.00 | 0.00 | 0.01 | 0.04 |
| NIM | 1,905,976 | 0.01 | 0.02 | -0.02 | -0.00 | 0.00 | 0.02 | 0.03 | 0.05 |
| 3-year asset growth | 2,141,245 | 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 | 0.67 | 0.33 | 0.23 |
| External | 238 | 0.87 | 0.57 | 0.53 |
| Fraud | 279 | 0.70 | 0.41 | 0.30 |
| Governance | 88 | 0.90 | 0.53 | 0.49 |
| Losses | 264 | 0.53 | 0.40 | 0.25 |
| Run | 20 | 0.15 | 0.18 | 0.08 |
| Not classified | 1859 | 0.81 | 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 | | 0.32*** |
| | | (0.10) |
| N | 2426 | 2218 |

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:** ***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 | 522 | 0.64 | 0.39 | 0.26 |
| Early Federal Reserve | 632 | 0.83 | 0.53 | 0.49 |
| Great Depression | 1677 | 0.79 | 0.54 | 0.52 |
| All | 2831 | 0.77 | 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).

**Table A.6:** ***Predicting Bank Failures: 1880-1904*.**

| Horizon $h$ | Fail in next year | | | | | 3 years | 5 years |
|---|---|---|---|---|---|---|---|
| Withdrawals before failure | | | | | >7.5% | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| ***Solvency:*** | | | | | | | |
| - NPL/Loans | 10.51*** | | 3.91*** | 3.66*** | 3.02*** | 10.21*** | 13.92*** |
| | (0.01) | | (0.01) | (0.01) | (0.01) | (0.01) | (0.02) |
| - Dividend Payout Restricted | 1.95*** | | 0.88*** | 0.85*** | 0.71*** | 1.85*** | 2.16*** |
| | (0.00) | | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| ***Funding:*** | | | | | | | |
| - Wholesale Funding/Assets | | 17.23*** | 7.95*** | 7.87*** | 3.64*** | 20.78*** | 32.42*** |
| | | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.02) |
| ***Solvency* $\times$ *Funding:*** | | | | | | | |
| - NPL/Loans $\times$ WF/Assets | | | 303.70*** | 300.07*** | 175.19*** | 421.14*** | 432.65*** |
| | | | (0.17) | (0.17) | (0.12) | (0.27) | (0.34) |
| - Div. Restricted $\times$ WF/Assets | | | 42.76*** | 42.67*** | 24.26*** | 44.90*** | 38.47*** |
| | | | (0.03) | (0.03) | (0.02) | (0.04) | (0.05) |
| ***Bank Growth:*** | | | | | | | |
| - Q1 of Growth from t-3 to t | | | | 0.28*** | 0.16*** | 0.45*** | 0.41*** |
| | | | | (0.00) | (0.00) | (0.00) | (0.00) |
| - Q2 of Growth from t-3 to t | | | | 0.10 | 0.05 | 0.04 | -0.11 |
| | | | | (0.00) | (0.00) | (0.00) | (0.00) |
| - Q4 of Growth from t-3 to t | | | | 0.08 | 0.05 | 0.12 | 0.15 |
| | | | | (0.00) | (0.00) | (0.00) | (0.00) |
| - Q5 of Growth from t-3 to t | | | | 0.04 | -0.03 | 0.28** | 0.51*** |
| | | | | (0.00) | (0.00) | (0.00) | (0.00) |
| ***Aggregate Conditions:*** | | | | | | | |
| - GDP Growth from t-3 to t | | | | -0.63*** | -0.46*** | -1.80*** | -1.42*** |
| | | | | (0.00) | (0.00) | (0.00) | (0.00) |
| N | 73389 | 73510 | 73389 | 73316 | 73316 | 73316 | 73316 |
| No of Banks | 5141 | 5148 | 5141 | 5137 | 5137 | 5137 | 5137 |
| Mean of dep. var. | .38 | .38 | .38 | .38 | .19 | 1.1 | 1.7 |

Notes: This table presents OLS estimates of (2) with failure between $t$ and $t+h$ as the dependent variables for the 1870-1904 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.7:** ***Predicting Bank Failures: 1914-1928*****.**

| Horizon $h$ | Fail in next year | | | | | 3 years | 5 years |
|---|---|---|---|---|---|---|---|
| Withdrawals before failure | | | | | >7.5% | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| ***Solvency:*** | | | | | | | |
| - Surplus/Equity | -3.18*** | | -2.45*** | -2.04*** | -1.26*** | -5.88*** | -8.92*** |
| | (0.00) | | (0.00) | (0.00) | (0.00) | (0.01) | (0.01) |
| - Loans/Assets | 0.93*** | | 0.26** | 0.25** | 0.17* | 0.77*** | 1.23*** |
| | (0.00) | | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| ***Funding:*** | | | | | | | |
| - Time Deposits/Deposits | | 0.66*** | -0.39 | -0.26 | -0.42 | -0.21 | 1.17 |
| | | (0.00) | (0.00) | (0.00) | (0.00) | (0.01) | (0.01) |
| ***Solvency*** $\times$ ***Funding:*** | | | | | | | |
| - Surplus/Equity $\times$ Time Dep./Dep. | | | -2.42*** | -2.63*** | -1.50*** | -6.64*** | -10.19*** |
| | | | (0.01) | (0.01) | (0.01) | (0.01) | (0.02) |
| - Loans/Assets $\times$ Time Dep./Dep. | | | 4.54*** | 4.37*** | 3.11*** | 12.38*** | 19.86*** |
| | | | (0.00) | (0.00) | (0.00) | (0.01) | (0.01) |
| ***Bank Growth:*** | | | | | | | |
| - Q1 of Growth from t-3 to t | | | | 0.96*** | 0.62*** | 2.38*** | 3.23*** |
| | | | | (0.00) | (0.00) | (0.00) | (0.00) |
| - Q2 of Growth from t-3 to t | | | | 0.09 | 0.07 | 0.31* | 0.62** |
| | | | | (0.00) | (0.00) | (0.00) | (0.00) |
| - Q4 of Growth from t-3 to t | | | | -0.02 | -0.00 | -0.16 | -0.23 |
| | | | | (0.00) | (0.00) | (0.00) | (0.00) |
| - Q5 of Growth from t-3 to t | | | | -0.04 | -0.07 | -0.15 | 0.19 |
| | | | | (0.00) | (0.00) | (0.00) | (0.00) |
| ***Aggregate Conditions:*** | | | | | | | |
| - GDP Growth from t-3 to t | | | | -1.02*** | -0.68*** | -3.81*** | -6.82*** |
| | | | | (0.00) | (0.00) | (0.00) | (0.00) |
| N | 69156 | 63137 | 62328 | 62214 | 62214 | 62214 | 62214 |
| No of Banks | 9151 | 9066 | 9055 | 9053 | 9053 | 9053 | 9053 |
| Mean of dep. var. | .53 | .56 | .55 | .55 | .34 | 2.2 | 4.6 |

Notes: This table presents OLS estimates of (2) with failure between $t$ and $t+h$ as the dependent variables for the 1914-1928 sample. In addition to the reported predictor variables, we also include the log of a bank's age. 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: 1929-1934***.

| Horizon $h$ | Fail in next year | | | | | 3 years | 5 years |
|---|---|---|---|---|---|---|---|
| Withdrawals before failure | | | | | >7.5% | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| ***Solvency:*** | | | | | | | |
| - Equity/Assets | -6.18*** | | -6.28*** | -9.25*** | -4.43*** | -40.94*** | -53.53*** |
| | (0.01) | | (0.01) | (0.01) | (0.01) | (0.03) | (0.03) |
| - Surplus/Equity | -7.31*** | | -2.91*** | -1.65*** | -1.12*** | -9.01*** | -9.22*** |
| | (0.01) | | (0.01) | (0.01) | (0.00) | (0.01) | (0.01) |
| - Dividend Payout Restricted | 2.21*** | | 1.34*** | 1.14*** | 0.47* | 1.55** | 0.36 |
| | (0.00) | | (0.00) | (0.00) | (0.00) | (0.01) | (0.01) |
| - Loans/Assets | 9.78*** | | 5.37*** | 5.19*** | 2.86*** | 11.09*** | 17.17*** |
| | (0.01) | | (0.01) | (0.01) | (0.00) | (0.01) | (0.01) |
| ***Funding:*** | | | | | | | |
| - Wholesale Funding/Assets | | 63.88*** | 102.76*** | 101.47*** | 50.57*** | 224.15*** | 219.41*** |
| | | (0.02) | (0.04) | (0.04) | (0.03) | (0.07) | (0.08) |
| ***Solvency × Funding:*** | | | | | | | |
| - Surplus/Equity × WF/Assets | | | -134.55*** | -132.21*** | -65.81*** | -182.60*** | -140.17*** |
| | | | (0.09) | (0.09) | (0.07) | (0.17) | (0.19) |
| ***Bank Growth:*** | | | | | | | |
| - Q1 of Growth from t-3 to t | | | | 2.35*** | 1.10*** | 3.55*** | 4.09*** |
| | | | | (0.00) | (0.00) | (0.01) | (0.01) |
| - Q2 of Growth from t-3 to t | | | | 0.71** | 0.31 | 1.36*** | 1.61*** |
| | | | | (0.00) | (0.00) | (0.01) | (0.01) |
| - Q4 of Growth from t-3 to t | | | | -0.23 | -0.34 | -1.53*** | -1.82*** |
| | | | | (0.00) | (0.00) | (0.01) | (0.01) |
| - Q5 of Growth from t-3 to t | | | | -0.30 | -0.20 | -1.48*** | -2.03*** |
| | | | | (0.00) | (0.00) | (0.01) | (0.01) |
| ***Aggregate Conditions:*** | | | | | | | |
| - GDP Growth from t-3 to t | | | | -0.56 | 0.92** | 14.37*** | 31.17*** |
| | | | | (0.01) | (0.00) | (0.01) | (0.01) |
| N | 27749 | 27929 | 27697 | 27602 | 27602 | 27602 | 27602 |
| No of Banks | 7319 | 7322 | 7313 | 7304 | 7304 | 7304 | 7304 |
| Mean of dep. var. | 2.4 | 2.4 | 2.4 | 2.4 | 1.3 | 8.9 | 12 |

Notes: This table presents OLS estimates of (2) with failure between $t$ and $t+h$ as the dependent variables for the 1929-1934 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: 1959-2023.***

| Horizon $h$ | Fail in next year | | | | | 3 years | 5 years |
|---|---|---|---|---|---|---|---|
| Withdrawals before failure | | | | | >7.5% | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| ***Solvency:*** | | | | | | | |
| - Net Income/Assets | -52.91*** | | 11.97*** | 12.56*** | 2.83*** | 19.74*** | 20.77*** |
| | (0.00) | | (0.01) | (0.01) | (0.00) | (0.01) | (0.01) |
| ***Funding:*** | | | | | | | |
| - Time Deposits/Deposits | | 2.18*** | 4.34*** | 4.38*** | 0.91*** | 10.38*** | 13.10*** |
| | | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| ***Solvency*** $\times$ ***Funding:*** | | | | | | | |
| - NI/Assets $\times$ TD/Dep. | | | -352.34*** | -354.79*** | -79.12*** | -670.25*** | -715.14*** |
| | | | (0.02) | (0.02) | (0.01) | (0.03) | (0.04) |
| ***Bank Growth:*** | | | | | | | |
| - Q1 of Growth from t-3 to t | | | | 0.08*** | 0.00 | 0.27*** | 0.44*** |
| | | | | (0.00) | (0.00) | (0.00) | (0.00) |
| - Q2 of Growth from t-3 to t | | | | -0.06*** | -0.02* | -0.15*** | -0.18*** |
| | | | | (0.00) | (0.00) | (0.00) | (0.00) |
| - Q4 of Growth from t-3 to t | | | | 0.03* | 0.00 | 0.15*** | 0.29*** |
| | | | | (0.00) | (0.00) | (0.00) | (0.00) |
| - Q5 of Growth from t-3 to t | | | | 0.02 | 0.01 | 0.54*** | 1.32*** |
| | | | | (0.00) | (0.00) | (0.00) | (0.00) |
| ***Aggregate Conditions:*** | | | | | | | |
| - GDP Growth from t-3 to t | | | | -0.08 | 0.17*** | 0.20 | 1.99*** |
| | | | | (0.00) | (0.00) | (0.00) | (0.00) |
| N | 616284 | 614914 | 614914 | 604967 | 604967 | 604967 | 604967 |
| No of Banks | 22102 | 22099 | 22099 | 22073 | 22073 | 22073 | 22073 |
| Mean of dep. var. | .27 | .27 | .27 | .27 | .054 | .88 | 1.4 |

Notes: This table presents OLS estimates of (2) with failure between $t$ and $t+h$ 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.10:** ***Area Under the Curve by era and during major waves 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 | 0.943 | 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 (4) of Table A.6. In the last three columns of panel A, we use in-sample predictions based on the estimation using data from 1929-1935 in column (4) of Table A.8. In Panel B, we calculate the AUC based on the predictions based obtained from the model in column (4) of Table A.9.

# 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'g house, 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 | 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 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | National City, National Stock Yards. | O. J. Sullivan | R. D. Garvin | $3,664,800 | $6,532,834 | $733,004 | $3,678,840 | $123,007 | $14,732,491 | $750,000 | $150,000 | $45,440 | $12,983,612 | $750,000 | ........ | $53,439 | 1 |
| 2 | New Douglas, Prange | A. F. Prange | W. W. Prange | 107,457 | 50,000 | 64,219 | 16,019 | 4,386 | 242,081 | 25,000 | 10,000 | 837 | 206,244 | ........ | ........ | ........ | 2 |
| 3 | Oblong, First | S. F. Odell | J. B. McKnight | 786,318 | 83,500 | 208,704 | 210,440 | 76,380 | 1,365,342 | 75,000 | 50,000 | 21,563 | 1,144,859 | 73,860 | ........ | 60 | 3 |
| 4 | O'Fallon, First | E. H. Smiley | W. R. Dorris | 296,662 | 174,207 | 484,832 | 183,751 | 75,195 | 1,214,647 | 100,000 | 30,000 | 4,676 | 979,939 | 100,000 | ........ | 32 | 4 |
| 5 | Okawville, First | W. G. Frank | W. E. Friend | 151,758 | 79,547 | 307,394 | 44,503 | 5,173 | 588,375 | 50,000 | 10,000 | 7,526 | 470,830 | 50,000 | ........ | 19 | 5 |
| 6 | Okawville, Old Exchange | C. H. Merrick | F. Moehle | 88,300 | 76,675 | 216,049 | 67,929 | 4,889 | 453,842 | 50,000 | 10,000 | 14,951 | 328,891 | 50,000 | ........ | ........ | 6 |
| 7 | Pittsfield, First | L. C. King | F. A. Hicks | 650,876 | 251,425 | 166,315 | 206,835 | 113,931 | 1,389,352 | 125,000 | 125,000 | 41,325 | 998,602 | 99,280 | ........ | 175 | 7 |
| 8 | Ramsey, Ramsey | L. C. Thiele | J. E. Easterday | 137,655 | 51,250 | 43,077 | 68,692 | 14,762 | 315,436 | 25,000 | 25,000 | 7,675 | 232,761 | 25,000 | ........ | ........ | 8 |
| 9 | Raymond, First | J. E. McDavid | C. McNaughton | 431,989 | 35,588 | 116,659 | 34,659 | 41,646 | 660,541 | 50,000 | 10,000 | 763 | 494,282 | 25,000 | $80,496 | ........ | 9 |
| 10 | Robinson, Second | A. U. McCandless | A. H. Lodge | 1,190,820 | 485,556 | 327,905 | 432,586 | 67,348 | 2,504,215 | 150,000 | 37,500 | 33,989 | 2,188,976 | 93,750 | ........ | ........ | 10 |
| 11 | St. Francisville, Peoples | S. Gray | G. H. Corrie | 170,068 | 107,500 | 110,128 | 34,200 | 19,456 | 441,352 | 70,000 | 10,000 | 5,723 | 305,624 | 50,000 | ........ | 5 | 11 |
| 12 | Salem, Salem | J. C. Martin | A. H. Bachman | 353,021 | 968,786 | 1,324,844 | 360,591 | 71,420 | 3,078,662 | 100,000 | 24,000 | 56,830 | 2,822,645 | 75,000 | ........ | 187 | 12 |
| 13 | Sandoval, First | B. F. Holmes | H. H. Bellamy | 58,831 | 45,710 | 28,768 | 49,091 | 24,437 | 206,837 | 40,000 | 2,500 | 1,301 | 138,354 | 24,640 | ........ | 42 | 13 |
| 14 | Smithton, First | J. A. Miller | E. P. Baltz | 113,288 | 59,881 | 80,845 | 25,757 | 16,668 | 296,439 | 25,000 | 8,000 | 350 | 238,032 | 25,000 | ........ | 57 | 14 |
| 15 | Sorento, National | L. C. Dreiling | H. H. Holbrook | 10,902 | ........ | 9,491 | 30,302 | 5,532 | 56,227 | 25,000 | 1,850 | (d) 7,631 | 33,982 | ........ | 3,000 | 26 | 15 |
| 16 | Sparta, First | T. B. Stephenson | P. G. Brown | 168,354 | 95,550 | 53,236 | 178,157 | 30,215 | 525,512 | 50,000 | 25,000 | 11,078 | 389,401 | 50,000 | ........ | 33 | 16 |
| 17 | Staunton, Staunton | C. F. Hackman | J. W. P. Kerr | 85,469 | 82,293 | 237,000 | 64,862 | 15,841 | 485,465 | 50,000 | 10,000 | 26,387 | 349,032 | 50,000 | ........ | 46 | 17 |
| 18 | Sumner, First | G. W. Hill | O. D. Atkins | 38,933 | 59,787 | 148,707 | 81,973 | 8,685 | 338,085 | 25,000 | 5,000 | 674 | 281,707 | 25,000 | ........ | 704 | 18 |
| 19 | Vandalia, First | F. L. Rice | R. H. Sturgess | 234,469 | 428,738 | 170,332 | 202,269 | 68,789 | 1,104,597 | 100,000 | 25,000 | 19,369 | 860,078 | 100,000 | ........ | 150 | 19 |
| 20 | Vienna, First | W. L. Williams | F. E. Worrell | 213,432 | 100,181 | 33,951 | 57,696 | 59,123 | 464,383 | 60,000 | 25,000 | 2,812 | 317,130 | 59,340 | ........ | 101 | 20 |
| 21 | Waterloo, First | N. B. Pautler | J. F. Schmidt | 172,706 | 223,338 | 136,773 | 100,669 | 6,386 | 639,872 | 25,000 | 15,000 | 1,437 | 573,435 | 25,000 | ........ | ........ | 21 |
| 22 | Wayne City, First | J. F. Mateer | W. O. Allen | 88,400 | 52,700 | 33,908 | 35,121 | 33,126 | 243,255 | 45,000 | ........ | 1,436 | 171,768 | 25,000 | ........ | 51 | 22 |
| 23 | White Hall, White Hall | C. A. Ruckel | R. S. Worcester | 371,118 | 206,063 | 188,280 | 121,473 | 16,158 | 903,112 | 100,000 | 20,000 | 29,480 | 703,632 | 50,000 | ........ | ........ | 23 |
| 24 | Witt, Security | H. F. Fesser | H. S. Armentrout | 121,245 | 64,346 | 138,243 | 27,591 | 7,947 | 359,372 | 25,000 | 5,000 | 5,248 | 299,124 | 25,000 | ........ | ........ | 24 |
| 25 | Woodlawn, First | E. A. Hill | M. Wood | 68,828 | 47,522 | 44,461 | 95,669 | 9,520 | 266,000 | 35,000 | 2,000 | 3,282 | 200,718 | 25,000 | ........ | ........ | 25 |
| 26 | Wood River, First | O. F. Nagel | G. G. Guker | 237,024 | 92,269 | 170,906 | 123,661 | 50,285 | 674,145 | 50,000 | 50,000 | 2,571 | 521,416 | 50,000 | ........ | 158 | 26 |
| 27 | Wood River, Wood River | J. M. Olin | H. E. Paton | 261,407 | ........ | 55,577 | 129,894 | 69,034 | 515,912 | 60,000 | 30,000 | 10,786 | 415,126 | ........ | ........ | ........ | 27 |
| 28 | Worden, First | T. C. Unger | W. E. Meyer | 38,797 | 33,308 | 10,941 | 18,348 | 11,710 | 113,104 | 25,000 | 5,000 | 194 | 57,912 | 24,998 | ........ | ........ | 28 |
| 29 | Xenia, First | J. M. Tully | E. Kepp | 99,489 | 34,000 | 1,169 | 52,560 | 14,866 | 202,084 | 25,000 | ........ | 1,082 | 150,963 | 25,000 | ........ | 39 | 29 |
| 30 | Zeigler, First | F. G. Hitt | R. R. Frazier | 49,690 | 396,574 | 220,202 | 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.*

Form F.R. 105 — Call 186 (Rev. 12-47) December 30, 1967 - December 31, 1968

RCRI
RCON

Budget Bureau No. 55-R004

> **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 | | Dollars | Cts. | |
|---|---|---|---|---|
| 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 | | Dollars | Cts. | |
|---|---|---|---|---|
| 26. (a) Capital notes and debentures | | 3200 | | 26 (a) |
| (b) Preferred stock—total par value | | 3220 | | (b) |
| (No. shares outstanding ________ ) | | | | |
| (c) Common stock—total par value | | 3230 | | (c) |
| (No. shares authorized ________ ) | 3210 | | | |
| (No. shares outstanding ________ ) | | | | |
| 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

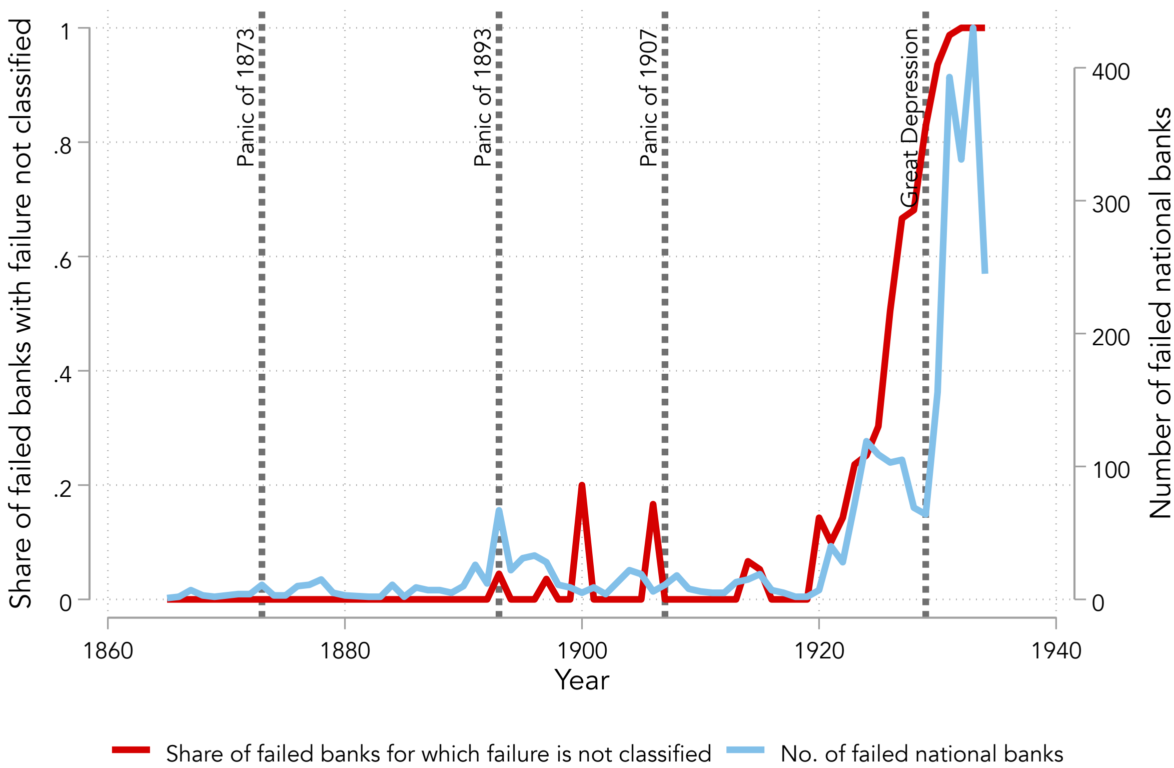
## B.2 Causes of Failures as Classified By the OCC

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 |

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| 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 |

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| 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 |