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FAILING BANKS

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ABSTRACT

Why do banks fail? We create a panel covering most commercial banks from 1863 through 2024 to study the history of failing banks in the United States. Failing banks are characterized by rising asset losses, deteriorating solvency, and an increasing reliance on expensive noncore funding. These commonalities imply that bank failures are highly predictable using simple accounting metrics from publicly available financial statements. Failures with runs were common before deposit insurance, but these failures are strongly related to weak fundamentals, casting doubt on the importance of non-fundamental runs. Furthermore, low recovery rates on failed banks' assets suggest that most failed banks were fundamentally insolvent, barring strong assumptions about the value destruction of receiverships. Altogether, our evidence suggests that the primary cause of bank failures and banking crises is almost always and everywhere a deterioration of bank fundamentals.

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1 Introduction

Bank failures are a recurrent feature of banking. In the United States, 19% of all national banks in existence from 1863 to 1934 and 13% of all commercial banks in existence from 1935 to 2023 failed at some point during these periods. Bank failures often lead to real economic disruptions (Bernanke, 1983), and there is a strong association between systemic banking crises featuring widespread bank failures and severe macroeconomic downturns (Reinhart and Rogoff, 2009).

What causes bank failures? Theory offers two main explanations. Under the *bank runs view*, bank failures are the consequence of runs in which depositors collectively withdraw from otherwise solvent (Diamond and Dybvig, 1983) or troubled but solvent banks (Goldstein and Pauzner, 2005). Bank runs are cited as an important cause of bank failures in prominent accounts of the Great Depression (Friedman and Schwartz, 1963), the 2008 Global Financial Crisis (Bernanke, 2018), and the bank failures in spring 2023. Under an alternative *solvency view*, bank failures are caused by poor fundamentals, such as realized credit risk, interest rate risk, or fraud, that trigger insolvency (e.g., Temin, 1976; Wicker, 1996; Calomiris and Mason, 1997; Admati and Hellwig, 2014; Gennaioli and Shleifer, 2018). While these two views are not mutually exclusive, the *bank runs view* emphasizes the runnable nature of bank liabilities as a key element to understanding bank failures, whereas, in the *solvency view*, failure is caused by losses, irrespective of whether a bank run occurs or not.

This longstanding debate raises several important questions. Which type of failures are empirically most relevant? Are bank failures primarily a result of bank runs or are they more commonly caused by insolvency? When runs do occur, do they commonly cause the failure of otherwise solvent banks, or do they primarily trigger the failure of insolvent banks?

Understanding the potential determinants of bank failures empirically, however, is challenging. Government interventions such as deposit insurance and lending of last

resort reduce the scope for bank runs to cause bank failures in modern times (Metrick and Schmelzing, 2021). A common argument for these interventions is precisely to prevent failures caused by runs, especially on otherwise solvent banks. Thus, observed bank failures in modern times may be biased towards failures involving poor fundamentals.

To overcome this challenge, we study the history of failing banks in the United States from 1863 to 2024. We construct a new database with balance sheet information for most banks in the U.S. since the Civil War. Our data consist of a historical sample that covers all national banks from 1863 to 1941 and a modern sample that covers all commercial banks from 1959 to 2024. Altogether, our data contain balance sheets for around 37,000 distinct banks, of which more than 5,000 fail. This long sample thus covers failures both before and after the founding of the Federal Reserve System and the introduction of deposit insurance from the Federal Deposit Insurance Corporation (FDIC). This dataset, therefore, allows us to study bank failures during historical episodes in which bank runs could plausibly have been a common cause of bank failures.

We present three sets of findings that inform the determinants of bank failures throughout the history of the U.S. banking system. First, we document that bank failures are strongly related to weak bank fundamentals. As a result, bank failures are highly predictable throughout the sample. Second, we show that large deposit outflows, indicative of bank runs, were common in pre-FDIC bank failures. Nevertheless, failures with bank runs are strongly connected to weak bank fundamentals. Third, we argue that low recovery rates in pre-FDIC failures imply that most banks that failed with a run were fundamentally insolvent, unless one assumes large bank value destruction from failure. Overall, our findings suggest that the *solvency view* goes a long way to understanding the primary cause of most bank failures.

We begin by documenting that failing banks are characterized by poor and deteriorating fundamentals. First, failing banks see a rise in non-performing loans and gradually deteriorating solvency several years before failure. Second, in the run-up to failure, banks

increasingly rely on expensive and risk-sensitive noncore funding, such as time deposits and wholesale funding. Furthermore, failing banks undergo a boom-bust pattern in assets during the decade before failure. Asset losses thus often follow a period of rapid loan growth.

These facts imply that bank failures are highly predictable based on weak fundamentals captured by accounting metrics from publicly available financial statements. The future probability of bank failure rises significantly in measures of insolvency risk and reliance on noncore funding. For example, a bank in the top 5th percentile of both insolvency risk and noncore funding reliance has a probability of failure over the next three years of over 25% in both the historical and modern sample. This amounts to a 10- to 25-fold increase in the probability of failure relative to the average bank, a large differential.

We formally quantify the extent of predictability by estimating simple regression models in which we predict whether a bank will fail based on proxies of bank fundamentals and macroeconomic conditions. We assess predictability based on the area under the receiver operating characteristic curve (AUC), a common measure of performance for binary classifiers. In the historical, pre-FDIC sample, the AUC for predicting failure within the next year is 86%, indicating a substantial degree of predictability. In the modern sample, after the introduction of deposit insurance, the predictability of bank failures is even higher, with an AUC between 90-95%. In both the historical and modern samples, the predictability of failures is typically nearly as high in pseudo-out-of-sample as in in-sample forecasting exercises.

Next, we show that bank runs were common in pre-FDIC bank failures. We compute the deposit outflow immediately before failure as the growth in deposits between the last pre-failure financial statement and failure. In the pre-FDIC sample, deposits in failing banks decline on average by 13% immediately before failure. In contrast, deposits fall by only 2% up to post-FDIC failures. Therefore, the deposit insurance regime features

significantly fewer failures involving bank runs. Nevertheless, while large deposit outflows were common in pre-FDIC failures, we find that failures with bank runs are as predictable as failures without runs. Thus, failures with runs are similar to other failures in that they tend to occur in banks with weak fundamentals.

Weak bank fundamentals not only predict individual bank failures. They also forecast waves of bank failures during systemic banking crises. We aggregate the out-of-sample forecasts of individual bank failure risk to predict the aggregate bank failure rate. The R^2 of a regression of the actual bank failure rate on the predicted aggregate failure rate is 40%. Thus, spikes in bank failures during systemic banking crises are, to a large extent, accounted for by deteriorating fundamentals.

In the final part of the paper, we examine recovery rates in pre-FDIC failures. We present a simple framework comparing a bank's recovery rate to its leverage to gauge whether a failed bank was fundamentally insolvent. Assessing the degree of insolvency is informative about whether a run could plausibly have caused the failure of a fundamentally solvent bank. However, it requires making assumptions about the wedge between the value of the assets in the bank and the value of the assets for the next best user. We first establish that recovery rates were low in pre-FDIC failures, averaging 52% of the book value of assets. We document that low recovery rates reflect, to a significant extent, unrealized losses on assets. Based on our framework, we then show that the majority of failed banks appear to be fundamentally insolvent. Moreover, the share of bank failures that involved a run on a bank that was *not* fundamentally insolvent—failures for which runs are a plausible cause of failure—is likely to be modest. For instance, under the extreme assumption that there is no value destruction from failure at all, runs on weak but solvent banks can account for less than 8% of pre-FDIC failures. Under an equally extreme assumption that failure destroys 20% of bank value, this share rises to 22%.

Taken together, our evidence suggests that the primary cause of bank failures is almost always and everywhere a deterioration of bank solvency. The erosion of a bank's

capitalization ultimately results in either a run or a supervisory decision to close a bank, with runs being more common in the historical data. Importantly, both depositors and supervisors seem slow to react to information about bank fundamentals, thus making bank failures predictable. The predictability of bank failures, in turn, suggests that non-fundamental, self-fulfilling runs on otherwise healthy banks, as in Diamond and Dybvig (1983), are an uncommon cause of bank failures, as such runs should strike randomly (see, e.g., Gorton, 1988; Greenwood et al., 2023).

Our finding that failures with runs typically occur in banks with weak fundamentals is consistent with the predictions of theories of fundamental-based panic runs (Goldstein and Pauzner, 2005; Morris and Shin, 2003; Rochet and Vives, 2004). However, our findings on low recovery rates also suggest that the majority of pre-FDIC failures with runs involved fundamentally insolvent banks. Thus, we argue that runs were more commonly an important trigger of failure for already insolvent banks than a primary cause of failure of potentially weak but solvent banks.

The high predictability of bank failures and the finding that runs typically close insolvent banks suggests that runs happen later than standard theoretical benchmarks would predict. In models of panic runs with rational and forward-looking depositors exposed to large losses from failure, bank failures cannot be highly predictable, as attentive depositors would act on this information and withdraw their funds, reducing the predictability in the first place. Thus, the fact that these banks have not failed yet and we can observe high predicted failure probabilities suggests that depositors are often slow to react to an increased risk of bank failure. This fact, in turn, points to a role for behavioral frictions such as neglect of downside risk (e.g., Gennaioli et al., 2012) and sleepy or inattentive depositors (see, e.g. Hanson et al., 2015; Jiang et al., 2023).

Finally, our interpretation that solvency rather than the runnable nature of bank liabilities is key to understanding banking failures is supported by classifications of causes of bank failures provided by contemporary bank examiners from the Office of the

Comptroller of the Currency (OCC). Notwithstanding the common occurrence of large deposit outflows in the run-up to failure, most pre-FDIC bank failures were classified by the OCC as being caused by losses, fraud, or external economic shocks. Despite popular narratives about bank runs playing a key role in the historical U.S. banking system, runs and liquidity issues account for less than 2% of failures classified by the OCC.

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, runs, 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; Metrick, 2024; Cipriani et al., 2024), and other episodes featuring bank runs (Iyer and Puri, 2012; Frydman et al., 2015; Iyer et al., 2016; Artavanis et al., 2022).¹ 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. Studying the close-to-complete history of the banking system in the United States allows us to generalize the insight that weak fundamentals are typically a necessary condition for bank failures across various institutional settings, both during financial crises and during quiet periods. The richness of the data further allows us to provide robust facts about the predictability of bank failures, deposit outflows before failure, and asset recovery rates in failure. Contrasting these facts with testable predictions of models of bank failures and runs, we argue that insolvency is the most common primary cause of failure, while runs most commonly trigger the failure of fundamentally insolvent banks. Moreover, while

¹Several 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 (e.g., Cole and Gunther, 1995, 1998; Wheelock and Wilson, 2000; Berger and Bouwman, 2013).

existing micro-level studies usually condition on a crisis, our long sample demonstrates that failures and banking crises are predictable out-of-sample.

Second, our paper is related to studies of financial crises using aggregate data. Within this literature, our paper relates most closely to studies on the nature of banking crises and the sources of bank failures and panics. Gorton (1988) and Calomiris and Gorton (1991) study banking panics in the National Banking Era and find that panics generally 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. This allows us to show that deteriorating fundamentals are necessary for both individual and widespread bank failures, including failures with runs. 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 and aggregate crises.

Roadmap. The paper proceeds as follows. [Section 2](#) provides a conceptual framework to guide our empirical analysis. [Section 3](#) describes the data. [Section 4](#) provides basic facts about bank fundamentals and bank failures. [Section 5](#) presents evidence on the predictability of bank failures. [Section 6](#) studies deposit outflows in failing banks and the predictability of bank failures with runs. [Section 7](#) shows that bank-level fundamentals predict the major waves of bank failures in the U.S. [Section 8](#) presents evidence on recovery rates and the share of fundamentally insolvent banks, and [Section 9](#) concludes.

2 Conceptual Framework

2.1 Theory

We organize our empirical analysis around two views of why banks fail: the *solvency view* and the *bank runs view*.

The *solvency view* posits that banks fail because they become insolvent. This occurs when the expected value of assets is too low to pay off all debt claims. Insolvency can occur due to asset losses from realized credit risk, which in turn may be driven by unexpected bad shocks to bank assets or due to excessive risk taking, perhaps driven by deeper governance issues. While solvency risk is most commonly associated with credit risk, banks can also become insolvent due to interest rate risk, which can reduce asset values and also increase funding costs. Importantly, a distinct feature of the solvency view is that the runnable nature of bank liabilities is not an important factor in causing bank failures. For example, Morris and Shin (2016) define solvency risk as the probability of failure in a counterfactual where withdrawals are not possible.

The *bank runs view*, in contrast, argues that the runnable nature of bank liabilities is an important element in explaining bank failures. In this view, bank runs play an important role in driving banks to insolvency and triggering failure. In the seminal model of Diamond and Dybvig (1983), banks finance illiquid assets with demandable deposits. While this benefits depositors by creating liquidity, coordination failure among depositors can lead to a self-fulfilling panic run on an otherwise solvent bank. The run leads the bank to liquidate assets at a loss, making the bank insolvent. In this model, the original cause of failure comes from the funding side and the behavior of depositors.² Because a run is one of two equilibria, this framework does not predict when runs will occur, but it raises the possibility that runs can cause failure randomly and should thus be unpredictable.

²Other theories where runs and failures start from depositor behavior include Bryant (1980), Allen and Gale (2000), and Peck and Shell (2003).

The Diamond and Dybvig (1983) framework is purposely stylized and abstracts from fundamental risk, such as asset losses. Indeed, existing time series and cross-bank studies find that banking panics and runs on individual banks generally follow bad news about fundamentals.³ Goldstein and Pauzner (2005) build on this idea and introduce shocks to bank assets in a model of bank runs. In this model, a panic run occurs when bank fundamentals are weak (see also Morris and Shin, 2000, 2003; Rochet and Vives, 2004). Formally, bank fundamentals θ are stochastic, and each depositor observes a slightly noisy signal of θ . When fundamentals are strong ($\theta > \bar{\theta}$) there is no risk of a run. If fundamentals are sufficiently weak ($\theta \leq \underline{\theta}$), the bank is insolvent and all depositors have an incentive to withdraw, irrespective of others' actions, resulting in failure through a "fundamental run." Yet, moderately weak fundamentals below a threshold θ^* (i.e., $\underline{\theta} < \theta < \theta^* < \bar{\theta}$) will trigger a "panic-based run" in the threshold equilibrium of Goldstein and Pauzner (2005), leading to bank failure. In this case, absent a run, the bank's asset realization would have been sufficient to pay all creditors. Thus, runs can amplify the effects of weak fundamentals.

Theories of bank runs underpinning the *bank runs view* usually have three central ingredients. First, depositors are rational and forward-looking. Hence, depositors immediately react to observable signals about sufficiently poor fundamentals (e.g., Allen and Gale, 1998). Second, there are externalities among depositors. The expectation of a run by other depositors increases the incentive of a given depositor to withdraw. Third, the run leads to value destruction. In most frameworks, value destruction comes from fire selling illiquid assets (Diamond and Dybvig, 1983). Value destruction can also occur through a decline in the franchise value of deposits (Drechsler et al., 2023; Jiang et al., 2023; Amador and Bianchi, 2024).

Models of fundamental-based panic runs, such as Goldstein and Pauzner (2005) and

³For aggregate time-series evidence, see, for example, Gorton (1988), Calomiris and Gorton (1991), Wicker (1996), and Baron et al. (2021). For bank-level evidence focused on specific crisis episodes, see Calomiris and Mason (1997), Calomiris and Mason (2003), and Blicke et al. (2024).

Morris and Shin (2000), illustrate that theories of bank runs and failures can incorporate elements from both views. Moreover, dynamic interactions between solvency and funding can amplify distress: declining solvency may trigger deposit outflows and rising funding costs, which in turn further weaken solvency. This spiral can generate a “slow run” that erodes a bank’s value (e.g., Lorenzoni and Werning, 2019; Llambias and Ordonez, 2024).⁴

Moreover, even if the root cause of bank failure is insolvency ($\theta < \underline{\theta}$), a run can be the mechanism that triggers failure (e.g., Diamond and Rajan, 2001) and governs the efficiency of the bankruptcy. A fundamentally insolvent bank may, absent market discipline or supervisory action, be able to operate for some time until it runs out of cash. Thus, under the solvency view, even if the runnable nature of bank liabilities is not the root cause of bank failure, it can be important in determining the exact timing and mechanics of failure.

2.2 Testable Implications

Our empirical analysis brings forward novel evidence that sheds light on the nature and causes of bank failures. Given that the solvency and bank runs views are not mutually exclusive, we note that it is difficult to completely separate the two explanations. Nevertheless, our goal is to establish facts and assess which elements of the two views are consistent with the observed patterns.

First, we study the *predictability of bank failures*. Strong predictability of failures based on weak bank fundamentals implies that fundamentals are an important factor in failures. Predictability is thus consistent with both the solvency view and the version of the bank runs view where panic-based runs are driven by weak bank fundamentals. However,

⁴Llambias and Ordonez (2024) model depositors who are partially inattentive. Adverse shocks to bank assets lead to gradual withdrawals. If the bank fundamentals fall below a certain threshold, then attentive depositors run. The model captures potential slow runs and the idea that failure can be preceded by persistently bad fundamentals because of depositor inattention, potentially generating predictability of runs and failures. For models of dynamic runs, see also He and Xiong (2012) and He and Manela (2016). Lorenzoni and Werning (2019) provide a model of slow runs for sovereign debt crises.

predictability is less consistent with models where non-fundamental runs bring down otherwise healthy banks, as in Diamond and Dybvig (1983).

Further, while models of fundamental-based panic runs predict that failure is related to weak fundamentals, evidence of strong predictability also cuts against the assumption of forward-looking rational depositors. In models of fundamental-based panic runs such as Goldstein and Pauzner (2005), rational and attentive depositors run immediately when a sufficiently low signal θ is realized. If bank failures could be easily anticipated based on public data, then rational depositors would act on this information and run, thus reducing predictability by triggering failure soon after the first signs of distress. Therefore, predictability of failures with runs suggests that frictions, such as inattention, slow down runs. However, we emphasize that predictability does not reject the possibility that runs can close weak banks that would have remained solvent absent a run.

Second, we study *deposit outflows* in failing banks. For a bank run to represent the cause of a bank failure, deposits must actually flow out of the bank before failure. In standard theories of bank runs, deposit outflows erode solvency by forcing banks to either liquidate their otherwise valuable assets or replace deposit funding with more expensive wholesale funding (Diamond and Dybvig, 1983; Allen and Gale, 2000; Goldstein and Pauzner, 2005). Hence, if a bank fails with only a minimal decline in deposits, a bank run is unlikely to be the cause of failure.

Third, we study *asset recovery rates* in failure. Under the solvency view, failing banks are insolvent, even absent the run. Fundamentally insolvent banks should thus have low asset quality and recovery rates in failure. In the bank runs view, the bank's asset realization would have been sufficient to pay off creditors absent the run. Therefore, asset quality in an otherwise solvent bank that fails because of the run should be less troubled than that of a fundamentally insolvent bank. An important challenge for translating this prediction into an empirical test is that the failure itself can destroy bank value due to a wedge between the value of the assets in the bank and the value for the next best user. For

example, the value of bank assets may be linked to the human capital of bank managers. While we cannot observe the value of a failed bank in the counterfactual where it did not fail, in [Section 8](#) we present a simple framework that allows us to make inferences about the share of failed banks that were insolvent absent a run, conditional on assumptions about the potential value destruction from failure.

3 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. The data provide annual bank-level information on broad balance sheet line items such as total assets, loans, deposits, and equity. In many years, the OCC also reports more detailed items that allow us to measure non-performing loans and various forms of non-deposit wholesale funding. However, the OCC did not require banks to report income statements. [Figure C.1](#) and [Figure C.2](#) in [Appendix C](#) provide examples of the original source.

Data on all national banks from 1867 until 1904 are digitized and provided by Carlson et al. (2022). For this project, we further digitize bank balance sheets from 1905 through 1941.⁵ In both cases, balance sheets are digitized using optical character recognition (OCR), applying the methods discussed in Correia and Luck (2023). We hand-check the OCR output, with particular attention to cases where accounting identities fail to hold. Moreover, we compile a list of all significant bank events and their dates—including chartering, liquidations, and receiverships—from 1863 to 1935 using data manually collected by van Belkum (1968), augmented by Huntoon (2023), and which we validate by using information from the 1941 “Alphabetical List of Banks” (Office of the Comptroller

⁵We also digitize additional data from 1863-1867. Moreover, note that while we collect data on national banks through 1941, most of our analysis is focused on data from before 1934 and thus before the FDIC became operational.

of the Currency, 1941), as well as the corresponding OCC Annual Reports.

We define a national bank as failed when the OCC appoints a receiver. This definition of failure includes banks that eventually exit receivership, restore solvency, and continue operating, as well as banks that exit receivership and wind down their operations in an orderly voluntary liquidation that imposes no losses to creditors. However, this definition excludes temporary bank closures that did not involve a receiver at some point. Moreover, we exclude instances where banks briefly suspend convertibility of their debt into cash and then reopen, as was common during banking panics of the National Banking Era (see, e.g., Jalil, 2015). This implies that we also exclude banks that averted receivership due to cooperation through, for example, bank clearinghouses. We emphasize this distinction, since the drivers of bank runs resolved by temporary suspension of convertibility may differ from those that lead to bank failures.

The OCC Annual Report also provides detailed information on the post-mortem developments of failed banks. These data provide information on the nominal amount of assets and deposits when a bank's business was suspended and a receiver was appointed. This allows us to estimate the outflow of deposits between the last call report and the day of failure. Furthermore, the OCC reports the funds ultimately collected by the receiver throughout the receivership proceedings. This allows us to calculate the recovery rate on assets and deposits. Finally, the OCC classified bank failures by the cause of failure for most failures between 1863 and 1937, except failures in 1932 and 1933. Further details on these data are provided in [Appendix C.2](#).

For the period before the founding of the FDIC, we rely entirely on data on national 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 other types of financial institutions that were chartered under state rather than federal law. National banks coexisted alongside state banks, trusts, and private banks, with the relative importance of

each type of institution varying over time. For example, national banks' market share of the entire banking market ranged from around 80% in the 1870s to around 45% in the 1930s (see [Figure A.2](#)). [Appendix A](#) provides further details on the historical evolution of the US banking system.

Data for modern sample (1959-2024). For the modern, contemporary banking system we use the Federal Financial Institutions Examination Council (FFIEC) Consolidated Reports of Condition and Income (the modern day "call report"). These data provide quarterly information on balance sheets and income statements on a consolidated basis for all commercial banks operating in the United States and regulated by the Federal Reserve System, the FDIC, and the OCC. Note that most existing research based on the call report uses the data starting from 1976 onwards (forms FFIEC 031, FFIEC 041, FFIEC 051). We extend our sample further back to 1959 (forms FFIEC 010 and 011), see [Appendix C.1](#) for more details. These data are digitally available at the Federal Reserve from 1959 through 2024. We also merge additional information on bank charters, such as bank founding dates, using the National Information Center (NIC) tables.

We complement the call report data with the FDIC's list of failing banks. This list documents all failures of FDIC member banks from 1934 through 2024. We define a bank failure as a bank closure that involves either a purchase of the failing bank with an assumption of some or all of its deposits or a liquidating receivership.⁶ We obtain the failure dates from the list of failing banks. Further, we obtain deposits and total assets at the time of resolution for failures from the FDIC's Failure Transaction Database. These data allow us to calculate deposit and asset growth immediately before failure for all failures since 1993.⁷

⁶Note that the FDIC's definition of failure is slightly broader. The FDIC defines a bank failure as the closing of a bank by regulators or an instance of open bank assistance. In the former case, the FDIC acts as receiver of the failed bank. In the latter, the FDIC provides financial assistance to prevent failure under a systemic risk exception; the bank would likely have failed without assistance. While we drop the latter, we note that all findings are robust to broadening the failure definition to include open bank assistance.

⁷For failures prior to 1993, the Failure Transaction Database reports total liabilities at failure but not

The financial statements we use are annual until 1941. After 1959, balance sheets were reported biannually, and then quarterly starting in 1976. Unless otherwise stated, we use annual data for our analysis to ensure comparability across different eras. When predicting bank failures, we also drop *de novo* banks since the determinants of failure for these banks can be different. We define *de novo* banks as banks younger than three years.

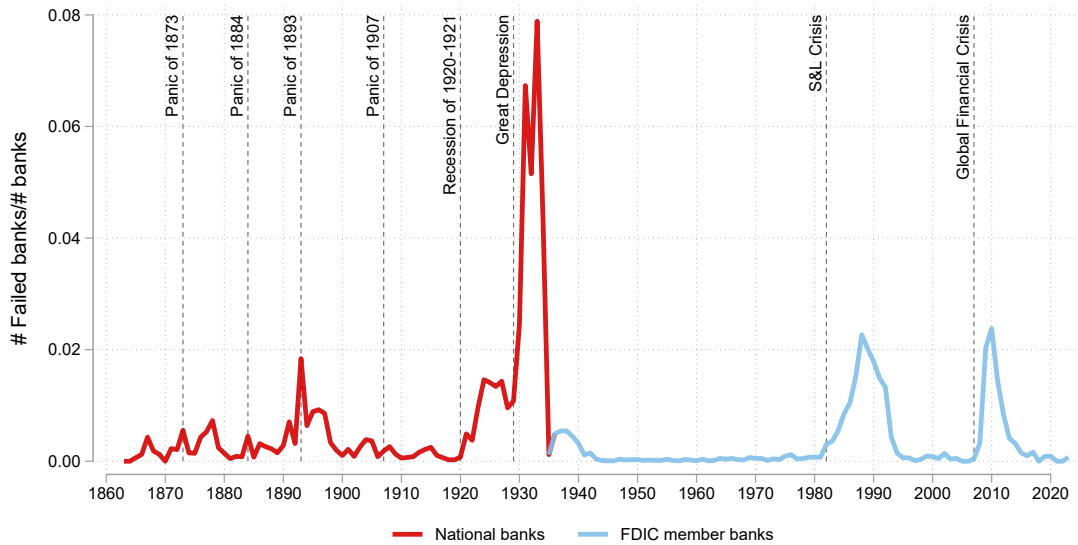
Altogether, our sample consists of 37,361 unique banks, 14,152 for the historical sample and 23,209 for the modern one.⁸ Of these banks, 5,120 fail at some point throughout the sample, with 2,887 failures before 1935 and 2,233 failures after 1959. [Figure 1](#) plots the rate of bank failures over time. The figure highlights that our sample includes the major financial crises in the history of the U.S., including the Great Depression and the 2008 Global Financial Crisis, as well as many quiet periods when bank failure rates were low. Moreover, our sample covers the period after the founding of the Federal Reserve in 1913 and the founding of the FDIC in 1933, as well as the period before either institution was operative. Hence, it spans an extensive period before the advent of a public lender of last resort, deposit insurance, or other forms of government interventions common in modern banking systems, such as restrictions on leverage or implicit and explicit government guarantees.

Other data. We obtain consumer price index data from Global Financial Data to deflate variables that we compare across time. Further, we use aggregate outcomes such as real GDP from Jordà et al. (2017) and Barro and Ursúa (2008) and banking crisis dates from Baron et al. (2021).

total deposits.

⁸Note that we assign different bank identifiers in the OCC data and the Call Report data, thus treating potentially the same bank as different entities in the historical and modern samples. Mechanically, this increases the total number of unique entities. About 3,700 national banks are counted twice as they operated in both periods.

Figure 1: Failing Banks, 1863-2024



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

4 Basic Facts: Fundamentals and Bank Failures

This section presents basic facts showing that weak fundamentals are strong predictors of bank failures across the entire 1863–2024 sample.

4.1 Measures of Bank Fundamentals

We define bank fundamentals as observable characteristics that proxy a bank’s financial health and survival prospects. We consider three bank fundamentals: insolvency risk, asset growth, and noncore funding. Insolvency risk directly proxies a bank’s distance to default. Asset growth captures the risk that rapid loan growth can lead banks to overextend themselves and incur future credit losses (Baron and Xiong, 2017; Fahlenbrach et al., 2018; Müller and Verner, 2023; Meiselman et al., 2023).

While measures of insolvency risk and asset growth directly capture situations where

bank losses reduce capitalization, we also use a funding-side measure capturing noncore funding. This measure proxies for increased reliance on costly funding, such as time deposits or non-deposit wholesale funding.⁹ The noncore funding measures can both contribute to and be a signal of deteriorating solvency. First, bank equity is in part valuable because banks have access to relatively cheap deposit finance (see, e.g. Egan et al., 2021). Bank equity value is reduced if a bank has to replace cheap demand deposits with non-core funding. Second, banks may use noncore funding to finance rapid and risky asset growth, presaging future losses (Hahm et al., 2013). Third, once a bank starts to realize losses, it may become reliant on noncore funding to fund these losses, so noncore funding is often a signal of losses (see, e.g., White, 1983; Calomiris and Mason, 1997; Calomiris and Carlson, 2022). Fourth, the reliance on noncore funding can be the consequence of ongoing liquidity pressures (for instance, due to a slow run) and make the bank more fragile to future funding shocks due to the increased funding fragility—both factors that erode bank equity value (Chen et al., 2024).

Before proceeding, we emphasize that the measures of fundamentals are endogenous and interrelated. In the context of assessing the predictability of bank failures, we do not take a stand on the causal relation between these measures and bank failures. For instance, a bank may appear to be in bad financial condition according to its solvency metric because it is relying on expensive forms of funding. At the same time, a bank may be only able to raise expensive forms of secured wholesale funding because it is approaching insolvency. Thus, these measures should be viewed as capturing observable signals in bank financial statements that indicate a banking business is more likely to be unproductive or potentially unviable.

The exact variables we use to measure insolvency risk and reliance on noncore funding differ across samples due to differences in data availability. For the pre-1934 sample, we

⁹Rates on noncore deposits such as wholesale deposits, time deposits, brokered deposits, and non-deposit wholesale funding are more sensitive to bank risk, interest rates, and market conditions (see, e.g., Martin et al., 2023; Drechsler et al., 2017).

measure insolvency risk by surplus profits over total equity. This measure is a proxy for bank income and capitalization.¹⁰ For the same period, we measure noncore funding by total assets net of total deposits (including unsecured interbank deposits), equity, and national bank notes. This captures expensive, non-deposit wholesale funding.¹¹ For 1959-2024, insolvency risk is measured by net income to assets, and noncore funding is measured by the sum of time deposits and wholesale funding relative to total assets.¹²

4.2 Insolvency Risk and Bank Failures

Figure 2 plots the probability of failure within three years conditional on a bank's fundamentals in year t . Panels (a) and (b) use insolvency risk as the measure of fundamentals for the historical pre-FDIC era (1863-1934) and the modern era (1959-2024). The probability of failure within the next three years rises with exposure to insolvency risk. The relation is generally nonlinear, with the risk of failure rising rapidly in the right tail. Moving from below the 50th percentile to above the 95th percentile in the measure of insolvency implies an increase in the probability of failure of 4pp in the historical sample (panel a) and 10pp in the modern sample (panel b).

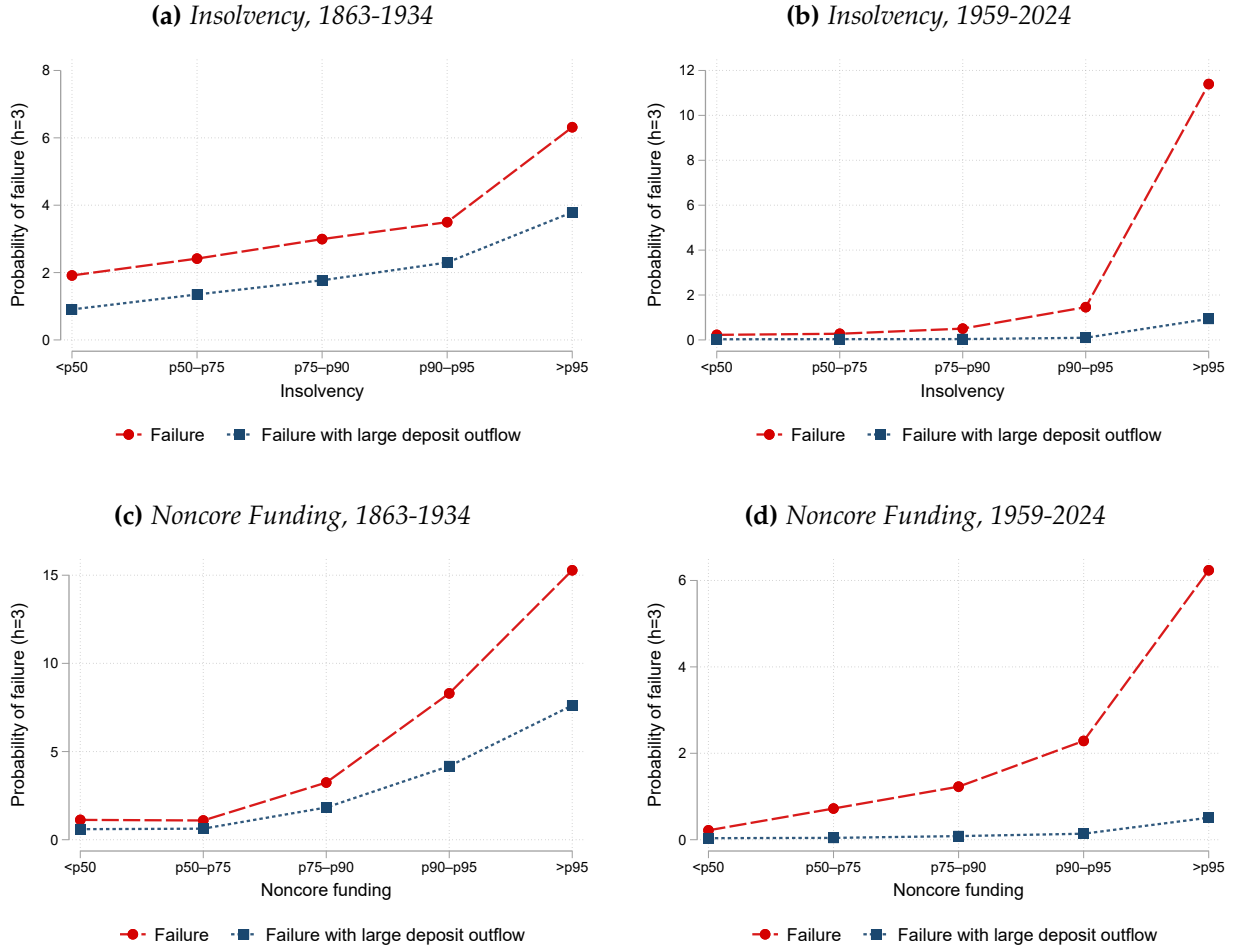
Insolvency risk is strongly related to bank failures in the cross section. How does insolvency risk evolve *within* failing banks? To understand the dynamics of losses and insolvency risk in failing banks before their failure, we estimate variants of the following

¹⁰In the OCC call reports for national banks, bank equity capital is divided into initial paid-in capital, undivided profits, and the surplus fund. Paid-in capital was fixed after the founding of a bank. Undivided profits reflect accumulated net earnings that have not yet been allocated to be paid out as dividends or transferred to the surplus fund. The surplus fund is retained earnings set aside from profits to increase bank capital. "Surplus profit" is the sum of undivided profits and the surplus fund. Thus, surplus profit is the portion of equity that varies with retained earnings and realized losses.

¹¹We verify that noncore funding effectively comprises the line items "Bills Payable" and "Rediscounts" in years in which the latter are reported. These line items represent forms of short-term, expensive, and secured wholesale funding—including borrowings from the Federal Reserve after 1914 (see, e.g., Carlson, 2025). Note that from 1905 through 1920, unsecured interbank funding and other liabilities are reported in the same line item. Hence, our noncore measure may under-report the use of secured wholesale funding for these years.

¹²For the historical sample, we do not include time deposits in noncore funding, as this item is only reported separately during 1915-1928.

Figure 2: Insolvency, Noncore Funding, and Future Probability of Bank Failure



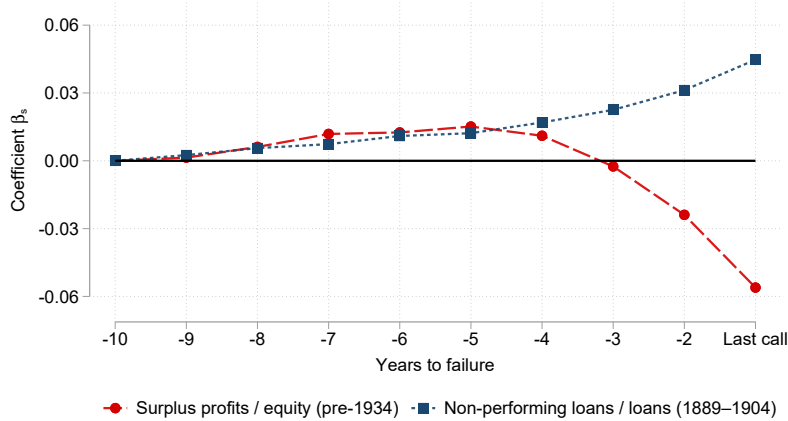
Notes: This figure plots the probability of bank failure within the next three years against the distribution of proxies for insolvency and noncore funding in year t . For the pre-FDIC era (1863-1934), insolvency is measured by surplus profit relative to equity. This measure is a proxy for bank income and capitalization. Noncore funding is measured by total assets net of total deposits (including unsecured interbank deposits), equity, and National Bank notes, all scaled by assets. For the Modern Era (1959-2024), solvency is measured by net income-to-assets, and noncore funding is measured by time deposits and wholesale funding (“Other Borrowed Money”) to total assets. Failures with large deposit outflows are defined as those where total deposits fall by more than 7.5% between the last call report and failure. In panels (a) and (c), failures with large deposit outflows are based on the 1880-1934 sample, as the OCC only reports deposits at the time of failure starting in 1880. In panels (b) and (d), failures with large deposit outflows are based on the 1993-2024 sample, as the FDIC only reports deposits at the time of failure starting in 1993.

specification:

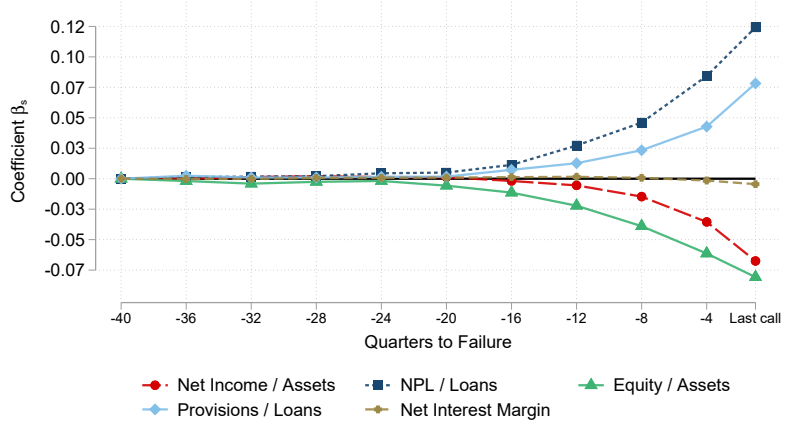
$$y_{b,t} = \alpha_b + \sum_{j=-10}^0 \beta_j \times \mathbf{1}_{j=t} + \epsilon_{b,t} \quad (1)$$

Figure 3: Losses and Solvency Dynamics in Failing Banks: 1863-2024

(a) 1863-1934



(b) 1959-2024



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 and the ten years before they fail. The figure reports the dynamics in failing banks relative to ten years before failure (the omitted period). In panel (a), the sample is restricted to banks that failed from 1863 through 1934. In panel (b), the sample is restricted to banks that failed from 1959 through 2024. In panel (a), surplus profit to equity is the sum of the surplus fund and undivided profits relative to total equity capital (paid-in capital, undivided profits, and surplus fund). Non-performing loans is proxied by the line item “Other real estate owned (OREO)” and is available for the 1889-1904 subsample. In panel (b), the net interest margin (NIM) is defined as total interest income net of interest expenses normalized by total assets.

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

Figure 3 presents the dynamics in indicators of loan losses and solvency in failing banks from estimation of Equation (1). Panel (a) presents the results for the 1863-1934 sample. Historically, provisioning rules were less strict, so equity was not immediately impacted when loans became non-performing. Nevertheless, failing banks see a gradual deterioration in surplus profits relative to equity, indicating negative profitability and declining capitalization. Moreover, failing banks see a gradual 5 percentage point rise in “Other Real Estate Owned,” a proxy for non-performing loans, indicating that the decline in capitalization is at least partly driven by realized credit risk.¹³

Panel (b) of Figure 3 plots the dynamics of solvency in failing banks for the 1959-2024 sample. In the five years before failure, failing banks see a 10-percentage-point rise in NPLs. This rise in NPLs translates into rising loan loss provisions, which results in a decline in realized net income. Thus, credit risk also plays an important role in the erosion of bank profitability in the modern sample. As a result, the equity-to-assets ratio declines considerably in the run-up to failure, falling by 8 percentage points. Altogether, throughout the sample from 1863-2024, failing banks see gradually rising losses and deteriorating solvency before failure.

¹³“Other Real Estate Owned” (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 as seized collateral. Below, in Table 6, we document that OREO as a share of loans in failing banks immediately before failure is significantly negatively correlated with asset recovery rates in failure. This measure is available for the 1889-1904 subsample.

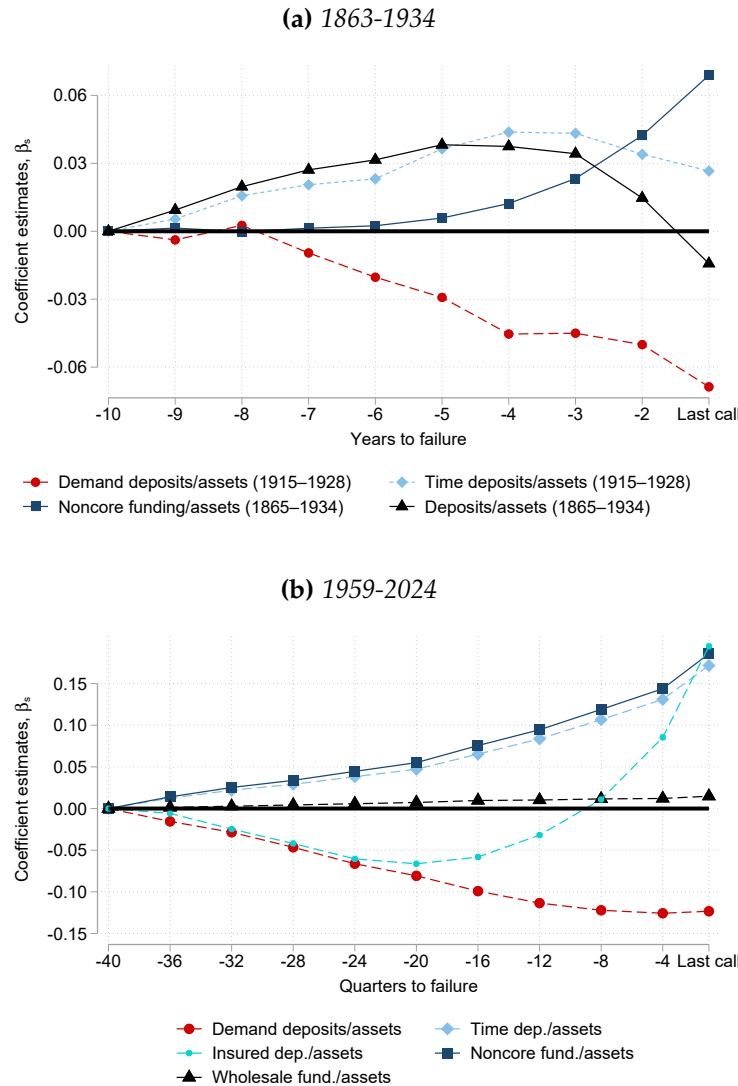
4.3 Noncore Funding and Bank Failures

Panels (c) and (d) in [Figure 2](#) plot the relation between noncore funding in year t and the probability of failure over the next three years. Reliance on noncore funding is strongly related to the future likelihood of failure. Noncore funding is an especially strong signal of failure in the historical sample. For example, moving from below the 50th percentile to above the 95th percentile in noncore funding is associated with an increase in the probability of failure of 14pp in the historical sample and 5.5pp in the modern era.

To understand the evolution of funding in failing banks, [Figure 4](#) presents estimates of (1) for various funding ratios. Panel (a) presents results for the historical 1863-1934 sample. Failing banks see a gradual rise in noncore funding relative to assets. For the subsample where we observe demand and time deposits separately (1915-1928), we see there is also an increase in time deposits, while demand deposits decline as a share of assets. Demand deposits, unlike time deposits, tend to be held by less price-sensitive retail investors and are a cheaper source of financing. Thus, failing banks increasingly rely on expensive forms of funding. In the two years before failure, as failing banks start to see rising losses, deposit funding as a share of total assets starts to decline and is replaced nearly one-for-one by more expensive noncore funding, likely reducing bank profitability. This finding is consistent with previous work showing that banks that experienced difficulties were often forced to rely on this more expensive type of funding (see, e.g., White, 1983; Calomiris and Mason, 1997; Calomiris and Carlson, 2022).

Panel (b) in [Figure 4](#) presents funding dynamics in failing banks for the modern sample. Similar to the historical sample, failing banks in the modern sample increasingly rely on noncore funding, which rises by 18% of assets in the decade before failure. Time deposits account for the largest increase. Wholesale funding also rises, though the increase is small relative to assets. In contrast, demand deposits decline as a share of assets in the decade before failure. As a result, failing banks see a gradual rise in interest expenses before failure (see [Figure B.1](#)).

Figure 4: Funding Dynamics in Failing Banks: 1863-2024



Notes: This figure shows the sequence of coefficients from estimating Equation (1) for various funding ratios. The sample is restricted to failing banks and the ten years before they fail. In panel (a), the sample is restricted to banks that failed from 1863 through 1934. In panel (b), the sample is restricted to banks that failed from 1959 through 2024. Further, in panel (b) we estimate the model using quarterly data but only plot the end of calendar year coefficients. In panel (a), noncore funding is measured by total assets net of the sum total deposits, equity, and National Bank Notes, all scaled by assets. Noncore funding effectively proxies for the “Bills Payable” and “Rediscounts” line items. Total deposits are available for the entire 1863-1934 sample. Time and demand deposits are reported separately for the 1915-1928 subsample. In panel (b), noncore funding is defined as the sum of time deposits and wholesale funding. 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.

While there is an increased reliance on noncore funding, in the modern sample, insured deposits simultaneously flow *into* failing banks in the five years before failure. This suggests that insured depositors do not discipline failing banks, potentially delaying failure.¹⁴ As we discuss further below, deposit dynamics differ substantially in failing banks before and after the introduction of federal deposit insurance. Despite this important difference, an important commonality is that failing banks increasingly rely on noncore funding throughout the sample.

4.4 Interaction of Insolvency and Noncore Funding

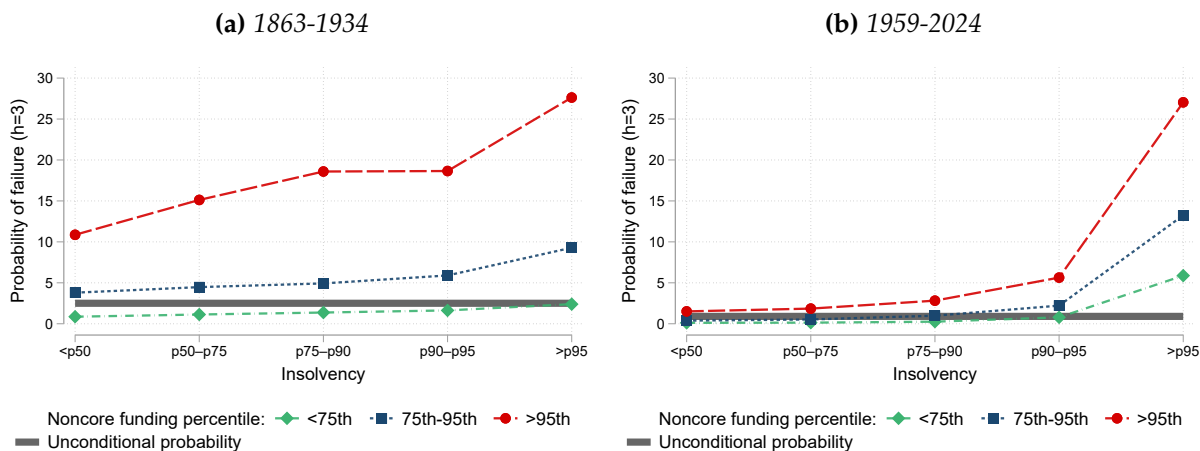
Are banks more likely to fail when they have both weak solvency and are reliant on noncore funding? A bank that has weak solvency proxies *and* relies on costlier and more risk-sensitive financing may see a hastier demise, as creditors raise the cost of financing or withdraw financing more quickly as losses mount. Moreover, as discussed above, noncore funding can proxy for exposure to insolvency risk, so the combination of the two measures could provide a stronger signal of impending bank failure.

Figure 5 depicts the probability of bank failure over the next three years across the distribution of insolvency by whether funding vulnerability is below the 75th percentile, between the 75th and 95th, or above the 95th 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 5th percentile of both insolvency and high funding vulnerability is 27% in the historical sample and 27% in the modern sample. These are large numbers, considering that the unconditional probability of failure over three years is 2.5% in the historical sample and 1% in the modern sample. Therefore, a bank with high insolvency risk

¹⁴These 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 noncore funding to finance rapid growth and subsequent losses 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).

and high funding vulnerability has a 10-20 times larger probability of failure than a randomly drawn bank. Overall, this illustrates that fundamental measures of insolvency and expensive noncore funding strongly predict future failure.

Figure 5: Interaction of Insolvency and Noncore Funding for Predicting Future Bank Failures



Notes: This figure plots the probability of bank failure within the next three years against the joint distribution of proxies for insolvency and noncore funding in year t . For the pre-FDIC period (1863-1934), insolvency is measured by surplus profits over equity. Noncore funding is measured by total assets net of total deposits, equity, and National Bank Notes, all scaled by assets. For the Modern Era (1959-2024), insolvency is measured by net income-to-assets, and noncore funding is measured by the sum of time deposits and wholesale funding (“Other Borrowed Money”) to total assets.

4.5 Asset Boom and Bust and Bank Failures

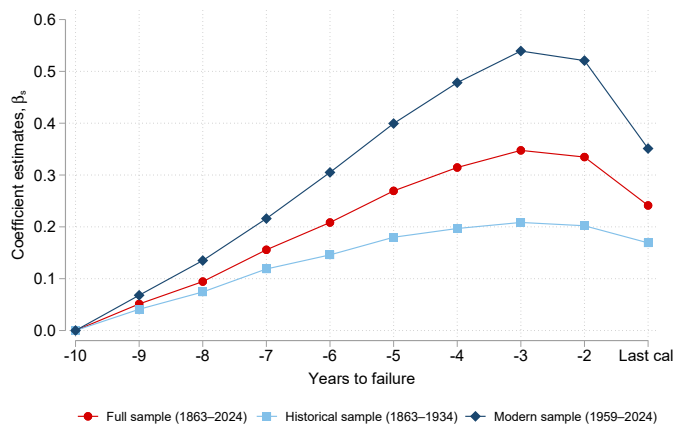
Why do banks experience gradually rising losses that eventually leads to heightened risk of failure? One reason is that rapid loan growth, potentially driven by overoptimistic expectations about default risk, is systematically associated with future credit losses (Bordalo et al., 2018; Greenwood et al., 2023).

Figure 6 presents the dynamics of asset growth in failing banks from estimating Equation (1) with the log of real total assets as the dependent variable. The figure reveals that total assets in failing banks follows a boom-and-bust pattern in the decade before failure.¹⁵ In the full sample, assets expand by 34% in real terms from ten years to three

¹⁵Appendix Figure B.7 shows that the relation between asset growth and future failure is non-monotonic

years before failure and then contract over the last two years before failure. The boom and bust pattern is present in both the pre-FDIC sample (1863-1934) and the modern sample (1959-2024), though it is significantly more pronounced in the modern period. The boom in assets is driven mainly by loans, rather than liquid assets (see Figure B.4). In the modern sample where we can observe loan types, we find that the strongest growth is in real estate lending, followed by C&I lending (see Figure B.5).

Figure 6: Asset Dynamics in Failing Banks: 1863-2024



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.

5 The Predictability of Bank Failures

Failing banks experience deteriorating solvency, increasing reliance on noncore funding, and an asset boom-bust in the decade before failure. These patterns are robust across different institutional settings and extend to the pre-FDIC period. This section shows that these systematic patterns imply substantial predictability of bank failures.

As discussed in Section 2, understanding the extent of predictability of bank failures

across quintiles of the asset growth distribution. Banks with rapid asset growth over the past three years ($t - 3$ to t) indeed have a heightened risk of failure over the next three years. Interestingly, banks in the lowest quintile of asset growth are also more likely to fail, likely because low growth signals a failing business.

is informative for two reasons. First, the degree of predictability of bank failures is informative about the importance of weak fundamentals in understanding bank failures. Second, the extent of predictability of bank failures in the historical sample can further help understand whether depositors are rational and forward-looking, acting quickly on signals of bank weakness, or whether frictions, such as inattention, slow down depositor reactions.

5.1 Empirical Specification

We conduct a formal prediction exercise to quantify the extent to which fundamentals can predict future failures, both in- and out-of-sample. Motivated by the basic facts in the previous section, we estimate simple predictive regression models of the following form:

$$\begin{aligned}
 \text{Failure}_{b,t+1 \rightarrow t+h} = & \alpha + \beta_1 \times \text{Insolvency}_{bt} & (2) \\
 & + \beta_2 \times \text{Noncore Funding}_{bt} \\
 & + \beta_3 \times \text{Insolvency}_{bt} \times \text{Noncore Funding}_{bt} \\
 & + \beta_4 \times \text{Asset Growth}_{bt} \\
 & + \beta_5 \times \text{Aggregate Conditions}_t + \epsilon_{b,t+1 \rightarrow t+h},
 \end{aligned}$$

where $\text{Failure}_{b,t+1 \rightarrow t+h}$ is an indicator variable that equals one if bank b fails within h years of the call report measured at time t . We assess predictability using both linear probability models and logit models to test the robustness of our results to the choice of functional form.

To predict bank failures, we use the same measures of insolvency and noncore funding as in [Section 4](#). We also consider the interaction between the insolvency and noncore funding measures, given the evidence in [Figure 5](#). Asset 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 for a non-linear relation between past growth and

failure. Furthermore, for Aggregate Conditions_{*t*}, we include aggregate real GDP growth and inflation over the same three-year period. These latter two measures are available in the same form throughout the entire 1863-2024 sample. Finally, we control for bank age, given existing evidence that younger banks are more likely to fail (White, 1984; Wheelock and Wilson, 2000). 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.¹⁶ Furthermore, we test both in-sample and pseudo-out-of-sample classification performance. The pseudo-out-of-sample AUC is constructed 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 . For pseudo-out-of-sample prediction exercises, we use the first 10 years of data as a training sample.

5.2 Main Predictability Results

Table 1 presents the in-sample and out-of-sample AUC statistics based on estimates of variants of Equation (2) for the historical pre-FDIC sample (1863-1934) and the modern sample (1959-2024). We present results for predicting failure at the 1, 3, and 5-year horizons. The corresponding regression estimates for each sample period are reported in

¹⁶For reference, the in-sample AUC for predicting financial crises in aggregate data based on credit and asset price growth is typically in the range 0.65-0.75 (e.g., Schularick and Taylor, 2012; Drehmann and Juselius, 2014; Baron et al., 2021; Greenwood et al., 2022; Müller and Verner, 2023). Similarly, Iyer et al. (2024) find an AUC of 0.73 when predicting local recessions with bank funding conditions.

Appendix Tables [B.4](#) and [B.5](#).

Bank failures are highly predictable based on the AUC metric. The in-sample AUC for the full specification in column (4) ranges from 86% in the historical sample to 95% in the modern sample. On their own, measures of insolvency and noncore funding both predict failures. Insolvency is relatively more predictive in the modern sample, while noncore funding has a higher AUC in the historical sample. The interaction between solvency and funding also boosts the predictive performance slightly. In the modern sample, where the predictability is extremely high, insolvency alone captures most of the predictive content of fundamentals.

The stronger predictive power of noncore funding relative to the insolvency measures in the historical sample has at least two potential explanations. First, funding pressures may play a more important role in pre-FDIC bank failures. Second, reliance on noncore funding can be more informative about a bank's distance to default than the insolvency metric. Creditors of weaker banks were more likely to lend through noncore funding (White, 1983; Calomiris and Mason, 1997). Furthermore, the informational content of book equity was lower, as banks were subject to less rigorous accounting standards and less strict provisioning rules in the historical sample.

There are several reasons for the stronger overall predictive performance in the modern sample. First, as just discussed, the quality of the accounting data is higher in the modern sample. 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 potentially harder to predict. Third, in the modern sample, bank failures are preceded by larger lending booms, which often imply predictable losses down the road. Finally, in the modern context, bank failures are, by and large, a supervisory decision (Correia et al., 2025). Frictions in the supervisory process, in turn, may delay bank failures, thereby increasing predictability.

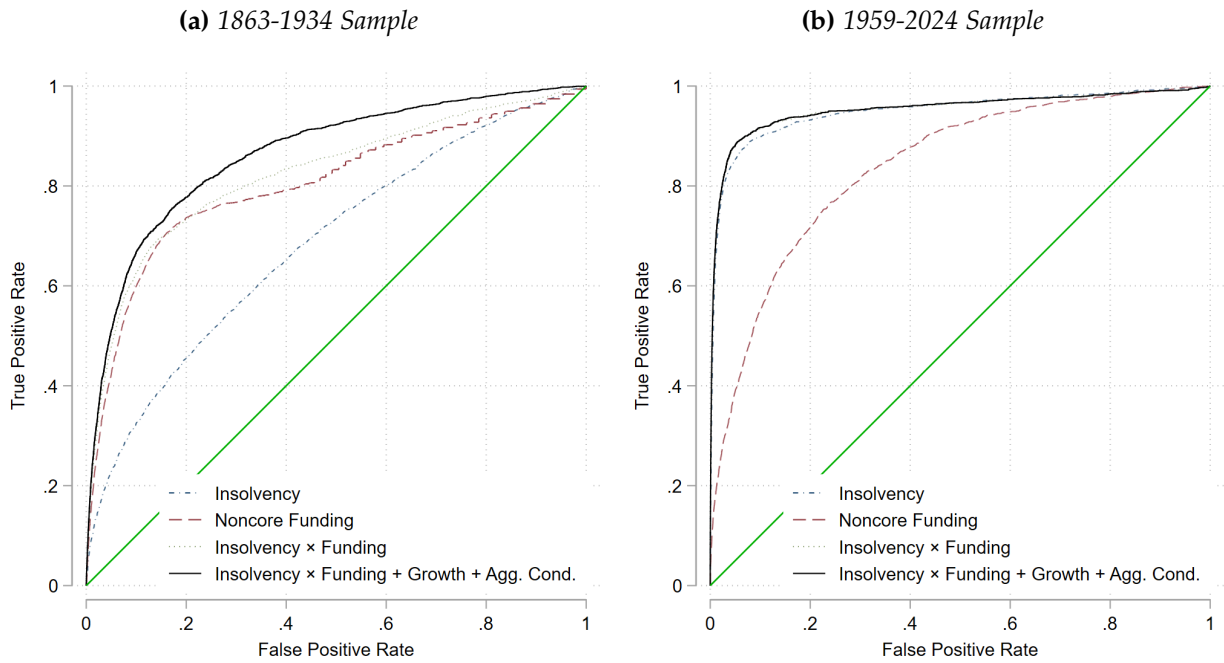
The pseudo-out-of-sample performance is nearly as strong as the in-sample predictive

Table 1: 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: Historical Sample (1863-1934)							
AUC (in-sample)	0.684	0.802	0.823	0.864	0.855	0.799	0.739
AUC (out-of-sample)	0.774	0.826	0.846	0.851	0.839	0.810	0.775
N	294574	294253	294247	290088	262636	290088	290088
No of Banks	12536	12535	12535	12428	11851	12428	12428
Mean of dep. var.	.79	.79	.79	.8	.45	2.5	4.1
Panel B: Modern Sample (1959-2024)							
AUC (in-sample)	0.949	0.846	0.954	0.953	0.932	0.889	0.831
AUC (out-of-sample)	0.942	0.792	0.946	0.945	0.922	0.869	0.805
N	633407	633404	633404	590645	215320	590645	590645
No of Banks	23107	23106	23106	22348	13900	22348	22348
Mean of dep. var.	.32	.32	.32	.34	.032	.97	1.5
Specification details							
Insolvency	✓		✓	✓	✓	✓	✓
Noncore funding		✓	✓	✓	✓	✓	✓
Insolvency × Noncore funding			✓	✓	✓	✓	✓
Growth & Aggregate conditions				✓	✓	✓	✓
Deposit outflow before failure					>7.5%		
Age controls	✓	✓	✓	✓	✓	✓	✓

Notes: This table reports the area under the receiver operating characteristic curve (AUC) across different specifications, samples, and horizons using in-sample and pseudo-out-of-sample classification. The corresponding regression coefficients underlying the models are reported in [Table B.4](#) (for Panel A) and [Table B.5](#) (for Panel B). Pseudo-out-of-sample AUCs are obtained by estimating the regression model with training data from 1863-1873 (Panel A), and 1959-1969 (Panel B), and iteratively expanding the sample for subsequent years. We drop banks without information on deposit outflows before failure in column (5). This restricts the sample period to 1880-1934 in Panel (A), as data on deposits at failure are not available before 1880. Similarly, column (5) in Panel B is restricted to 1993-2024, as deposits in failure are not available before 1993. [Table B.6](#) in the Appendix shows the AUC when using logit instead of linear probability models.

Figure 7: ROC Curves for Bank Failure Prediction



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

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

The high AUC statistics imply that bank failures can be classified with a high degree of accuracy. [Figure 7](#) presents a visualization of the tradeoff between true positives and false positives—the ROC curve—across specifications for the historical and modern samples. [Table B.11](#) reports true positive rates, false positive rates, true negative rates, and false negative rates for various classification thresholds. The ROC curves imply that a forecaster willing to accept a 10% false positive rate can achieve a true positive rate of 67% in the historical sample and 92% in the modern sample, again illustrating the strong predictability of bank failures.

5.3 Additional Predictability Results and Robustness

The estimated coefficients for the prediction models reported in [Table B.4](#) and [Table B.5](#) reveal several other interesting results. For subperiods of 1863-1934 sample, we also consider richer specifications using more detailed balance sheet line items that are only reported in specific periods (see [Table B.8](#), [Table B.9](#), and [Table B.10](#)). These regression estimates reveal that higher surplus profit to equity, higher loans to assets, lower equity to assets, and higher reliance on noncore forms of funding, such as bills payable and rediscounts, all significantly predict higher future rates of failure.

Bank asset growth is also significantly associated with failure. The relation is non-monotonic and changes with the horizon. 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*, as well as banks that contract the most.

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

Using richer, period-specific specifications generally leads to slightly better predictive performance (see [Table B.3](#)), but most of the predictability is summarized by the simpler baseline models summarized in [Table 1](#). [Table B.3](#) also shows that AUCs are substantial within subsamples of the historical sample, such as in the National Banking Era before the creation of the Federal Reserve (pre-1904), the Early Fed Era (1914-1928), and the Great Depression (1929-1933). Further, AUCs are similar across the bank size distribution (see [Table B.7](#)). Bank failures are predictable based on weak fundamentals for both small and large banks. The predictive performance is also similar across linear probability and logit models (see [Table B.6](#)).

Finally, in addition to evaluating predictive performance using the area under the receiver-operating characteristic curve (AUC), we also assess the precision-recall (PR) curve. The precision-recall curve traces the relationship between the proportion of predicted bank failures that are correct (true positives relative to true positives plus false positives) against recall (true positives relative to true positives plus false negatives, also known as the true positive rate). Precision-recall is informative when predicting a rare outcome, such as bank failures. [Table B.13](#) summarizes the area under the precision-recall curve (PR-AUC) across models and samples. Note that the PR-AUC has a different interpretation than the standard AUC. In particular, it is informative to compare the ratio of the PR-AUC to the unconditional probability of failure, as this base rate would be the PR-AUC of a naive model that classified all bank-year observations as failures.

Studying the precision-recall curve confirms the patterns discussed above. The PR-AUC is about 13 times higher than the failure rate for out-of-sample predictions from the historical sample, indicating moderately strong predictability (panels A and B, column 4). In the modern sample, the PR-AUC is over 70 times larger than the failure rate, indicating extremely strong classification performance.

6 Failures With Bank Runs

In this section, we discuss the role of bank runs in failures. We define bank failures with runs as those featuring a large deposit outflow immediately before failure. As discussed in [Section 2](#), large deposit outflows are a necessary, but not sufficient, condition for bank runs to be the cause of failure. We first show that large deposit outflows were common in bank failures before the FDIC. We then show that failures with bank runs are strongly predicted by weak bank fundamentals.

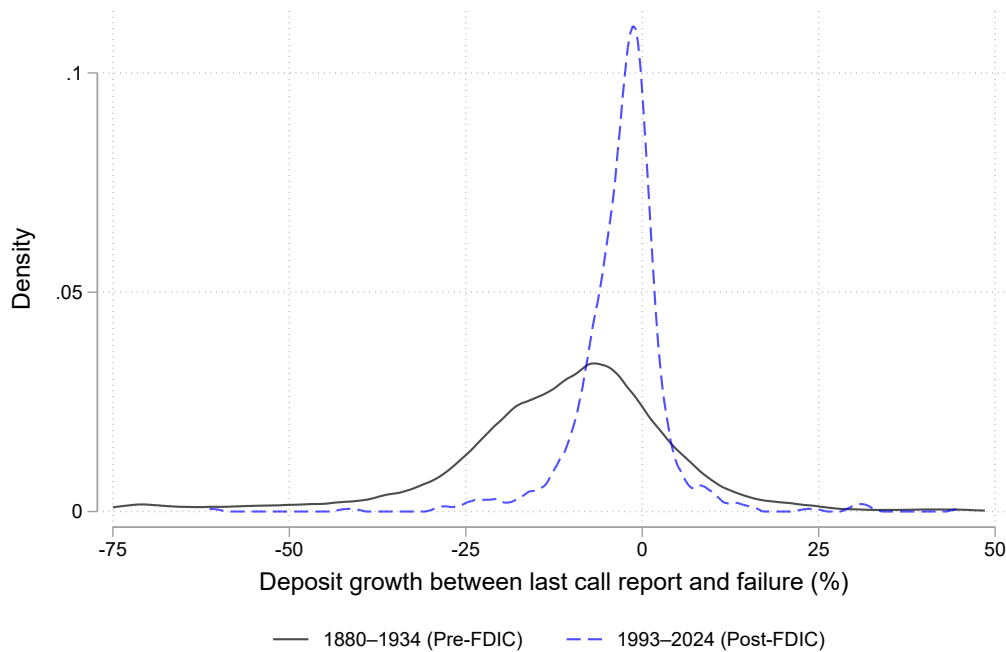
6.1 Deposit Outflows in Failing Banks

How large are deposit outflows before bank failures, and how does this vary with the presence of deposit insurance? We calculate deposit outflows immediately before failure as the growth in deposits from the last call report to the time of bank failure. For the historical period, the OCC reports deposits at suspension for all bank failures during 1880-1934. For the modern sample, we obtain deposits at failure during 1993-2024 from the FDIC Failure Transaction Database.

[Figure 8](#) visualizes the distribution of deposit growth immediately before failure for the pre- and post-FDIC samples. [Table 2](#) reports details on the distribution of deposit growth immediately before failure for various eras. On average, banks experience a 14% decline in deposits immediately before failure in the 1880-1934 sample. Moreover, 25% of all pre-FDIC failures were preceded by deposit outflows of more than 20%. Deposit outflows in failing banks were highest during the Great Depression. Before the banking holiday, deposits declined by an average of 21% between the last call and failure. Thus, large deposit outflows were quite common before the FDIC became operational. At the same time, large deposit outflows were not universal. In 26% of failures, deposits declined by less than 2.5%.

In contrast to the historical sample, average outflows before failure are much smaller in the modern sample. Deposit outflows immediately before failure averaged 2.5% for failures during 1993-2024, a sample that includes the 2008 Global Financial Crisis. Deposit outflows exceeding 20% are rare in the modern sample and only occur in 3% of all failures. These patterns are in line with deposit insurance insulating a large share of depositors from losses, reducing the incentives for deposit withdrawals before failure. Indeed, [Figure 4](#) shows that failing banks in the modern sample see a net inflow of insured deposits.

Figure 8: Deposit Outflow Immediately before Bank Failure



Notes: This figure shows the distribution of the growth in deposits between the last call report from before failure and the deposits reported in failure. Deposit growth is trimmed at -75% and 50%. We include failures from 1934 in the pre-FDIC sample. Even though the FDIC was founded in 1933, many receiverships in 1934 were associated with suspensions in 1933 (see [Appendix A](#)).

6.2 Predictability of Failures with Large Deposit Outflows

Before the introduction of deposit insurance, bank failures were commonly associated with bank runs. This suggests that the bank runs are relevant for understanding bank failures. As discussed in [Section 2](#), there are at least three possibilities. First, non-fundamental bank runs could cause the failure of solvent banks (Diamond and Dybvig, 1983). Second, panic runs could cause the failure of weak but solvent banks (Goldstein and Pauzner, 2005; He and Xiong, 2012). Or, third, fundamental runs could be the trigger for the failure of insolvent banks.¹⁷

To make progress in distinguishing between failures from non-fundamental runs and runs based on weak fundamentals, we next investigate whether failures with bank runs

¹⁷A fourth possibility that is difficult to test is that runs simply occur in response to news of imminent bank failure.

Table 2: Deposit Growth in Failing Banks Immediately before Failure

Era	Average	Share of failures with deposit growth falling within...						N
		<-30%	[-30,-20%)	[-20,-7.5%)	[-7.5,-2.5%)	[-2.5,0%)	>0%	
Panel A: Pre versus Post-FDIC								
1880-1934 (Pre-FDIC)	-13.71	0.13	0.12	0.33	0.16	0.07	0.19	2729
1993-2024 (Post-FDIC)	-2.55	0.01	0.02	0.13	0.30	0.30	0.24	546
Panel B: By Era								
1880-1913 (NB Era)	-14.40	0.18	0.16	0.32	0.13	0.04	0.17	499
1914-1918 (Early Fed)	-15.89	0.13	0.14	0.38	0.18	0.06	0.11	672
1929-1933 (Depr., pre-Hld.)	-21.19	0.17	0.16	0.44	0.14	0.05	0.04	962
1933-1934 (Depr., post-Hld.)	1.39	0.01	0.02	0.10	0.21	0.13	0.53	596
1993-2006	-5.64	0.08	0.11	0.33	0.21	0.08	0.19	63
2007-2024	-2.14	0.00	0.01	0.10	0.32	0.33	0.25	483

Notes: This table reports the percent change in nominal deposits from the last call report before failure to the time of failure. From 1880 through 1934, deposits in failure are as reported in the OCC annual reports table on national banks in receivership, which records deposits “at date of suspension.” After 1992, we use deposits in failure as reported in the FDIC’s Failure Transaction Database. *N* indicates the number of bank failures for which we match both deposits before failure and at suspension. In Panel B, we split the Depression sample into failures before and after the banking holiday in March 1933 due to the different nature in failures across those episodes (see, e.g., Jaremski et al., 2023). Deposit growth is clipped at 100%.

are less connected to weak fundamentals than other bank failures. [Figure 2](#) reveals that failures with large deposit outflows are related to weak fundamentals. In particular, [Figure 2](#) shows that the conditional probability of failure with large deposit outflows over the next three years is increasing in measures of insolvency and noncore funding, similar to all failures. We classify failures with large deposit outflow as those with outflows of more than 7.5% between the last call report and failure. The cutoff is necessarily arbitrary, but the results are robust to different cutoff choices. In the historical sample, moving from healthy fundamentals (below the 50th percentile) to high insolvency or funding vulnerability is associated with an increase in the probability of failure similar to the increase for all failures. While failures with large deposit outflows are rare in the modern sample, these failures are also associated with weaker fundamentals.

To reinforce this point, we estimate [Equation \(2\)](#) separately for failures with large deposit outflows. Comparing columns (4) and (5) in [Table 1](#) reveals that the predictive

performance of fundamentals is nearly identical for bank failures with large deposit outflows as for all failures. In the historical sample, the in-sample AUC is 86% both for failures with large deposit outflows and all failures. [Table B.3](#) shows that the AUCs for predicting failures with runs is slightly higher than for all failures using richer period-specific models for the National Banking Era (1880-1904) and the Early Federal Reserve Era (1914-1928), while the AUC for predicting failures with runs is slightly lower for the Great Depression. On balance, throughout the sample before deposit insurance, failures with runs are approximately as predictable as other failures.

Thus, the failures associated with large deposit outflows—failures that likely involved runs—are not wholly unexpected events that are disconnected from fundamentals. The high predictability of failures with large deposit outflows cuts against the view that failures were often caused by non-fundamental runs that brought down solvent banks randomly. This pattern also holds for the pre- Federal Reserve and pre-FDIC sample, when non-fundamental runs were in principle possible. Instead, it suggests that runs either caused the failure of weak but solvent banks or occurred in *ex ante* insolvent banks. This finding generalizes insights from existing empirical studies that have focused on studying specific panic episodes (see, e.g., Wicker, 1996; Calomiris and Mason, 1997, 2003) and establishes that weak fundamentals are typically a necessary condition for a bank to fail, even in the absence of a government safety net.

6.3 Depositor Inattentiveness before Deposit Insurance

The predictability of bank failures indicates that weak banks have a high in-sample predicted probability of failure. In [Figure 2](#) and [Figure 5](#), we saw that the predicted probability of failure exceeded 25% for the most vulnerable banks. [Appendix Table B.14](#) reports the distribution of out-of-sample predicted probabilities of failure for failing banks in the year before failure for the historical pre-FDIC sample. More than 48% of pre-FDIC failures have a predicted probability of failure over the next three years

in excess of 20% in the year before failure, compared to the unconditional three-year probability of 2.5%, using the relatively richer, period-specific regression models. Further, more than 34% of all failures are associated with a predicted probability of failure over three years exceeding 40%, a very high likelihood of failure for an individual bank.

The high predicted failure probabilities suggest that depositors are slow to react to the increased risk of bank failure. This, in turn, points to a role for behavioral frictions such as inattentive depositors or neglect of downside risk (e.g., Gennaioli et al., 2012; Jiang et al., 2023; Llambias and Ordóñez, 2024). Importantly, high predicted probabilities do not rule out the importance of coordination or the role of panic-based runs in causing the failure of weak but solvent banks. However, they do suggest that bank runs potentially happen later than theoretical benchmarks would suggest.

To illustrate the potential implication of the high predicted probabilities, recall that the information we use to estimate the probability of failure is public and therefore available to contemporary depositors. Moreover, depositor loss rates before the establishment of the FDIC were substantial, averaging 34% for pre-FDIC bank failures (see [Table B.18](#)).¹⁸ Appendix [Table B.14](#) presents a simple calculation of the excess returns that a risk-neutral and a risk-averse depositor would require to be compensated for holding deposits in these failing banks. Depending on the degree of risk aversion assumed, we find that between one-fifth and one-half of all failing banks would have faced a required annual excess return above 5% on their unsecured debt financing. While we do not have data on deposit rates, Cox (1967) shows, based on a sample of national banks in 1929, that essentially no bank paid such high interest rates on deposits. We speculate that such high levels of interest rates were not likely to be offered by weak banks, but rather that the high predicted probabilities of failure are a result of depositor inattention or other information frictions.

¹⁸This is a conservative estimate that does not account for the time value of money, as depositors often had to wait several years before obtaining this recovery rate (see [Figure B.10](#)).

7 Fundamentals and Aggregate Waves of Bank Failures

Individual bank failures, including those accompanied by runs, are predictable based on past fundamentals. Does the predictability at the micro level extend to forecasting aggregate waves of 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, 2000).

We find no evidence that fundamentals are less predictive of bank failures during crises. The AUC for predicting bank failures is similar during times of major banking crises as for the overall sample (see [Table B.15](#) in the Appendix). Therefore, fundamentals perform well in ranking which banks are likely to fail during crises, cutting against failures driven by indiscriminate panics.

Second, crises may feature *excess failures* beyond what fundamentals predict 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). Amplification can also occur through contagion that triggers funding pressure and runs on weak banks. These amplification mechanisms can increase the fundamental threshold at which banks fail, leading more banks to fail than would otherwise occur.

We examine whether deteriorating fundamentals can forecast the aggregate rate of bank failures, including spikes in bank failures during systemic banking crises. To do this, we obtain the pseudo-out-of-sample predicted probability of failure for each bank and year $\hat{p}_{b,t+1|t}$ from estimation of [Equation \(2\)](#) using data only up to year t . As the baseline,

we use the model in column (4) from [Table 1](#), namely the model with Insolvency_{bt} , $\text{Noncore Funding}_{bt}$, their interaction, Asset Growth_{bt} , and $\text{Aggregate Conditions}_t$. We then compute the average predicted failure rate $\bar{p}_{t|t-1} = \sum_{b \in B_{t-1}} w_{b,t-1} \hat{p}_{b,t|t-1}$, where w_{bt} is the weight on bank b at time t and B_t is the set of all banks in year t . As in [Table 1](#), we use an initial training sample of 10 years and estimate $\bar{p}_{t|t-1}$ separately for the 1863-1934 and 1959-2024 samples due to differences in data availability. We weight banks equally. Results are similar when weighting banks by size. We present baseline results from linear probability models, but show robustness to using logit models in the appendix.

Table 3: Fundamentals Predict Aggregate Rate of Bank Failures

Dependent variable	Aggregate Failure Rate			
	(1)	(2)	(3)	(4)
Predicted failure rate, $\bar{p}_{t t-1}$	1.25*** (0.24)	1.58*** (0.29)	0.97*** (0.15)	0.91*** (0.12)
Constant	0.08 (0.05)	0.07 (0.13)	0.06 (0.04)	0.09*** (0.03)
N	117	61	55	111
R^2	0.40	0.38	0.81	0.59
Sample	Full	1874-1934	1970-2024	Exclude 1929-1934

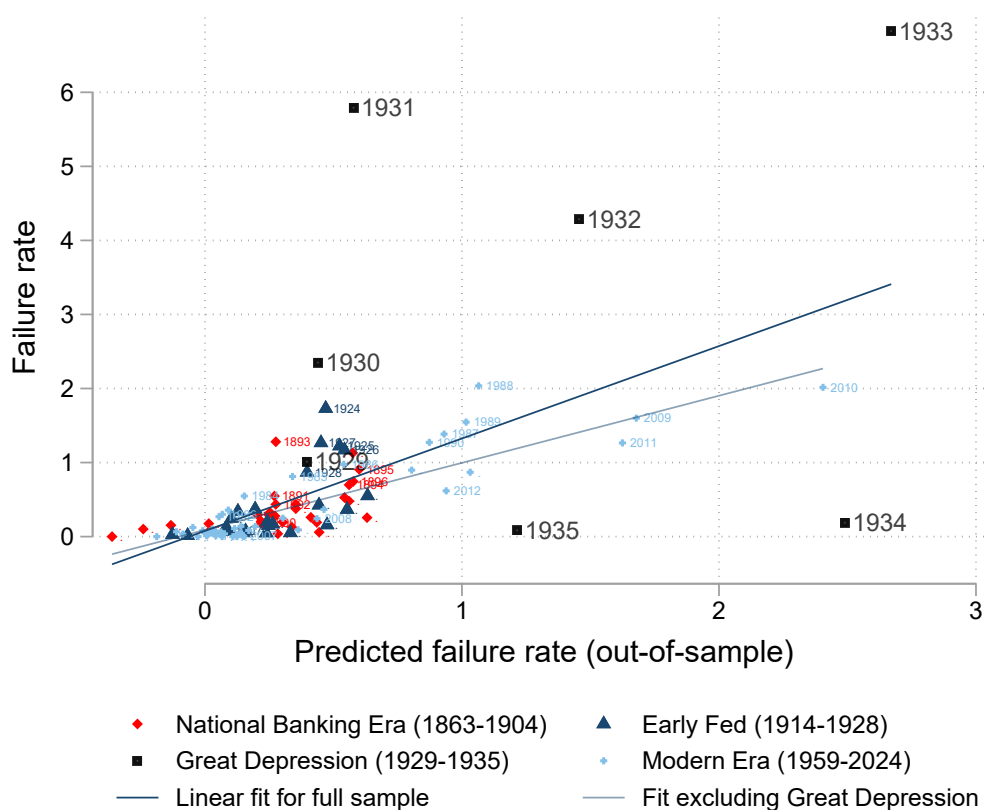
Notes: This table presents time series regressions of the annual aggregate failure rate in year t on the average predicted failure rate $\bar{p}_{t|t-1}$. The average predicted failure rate is constructed out-of-sample using an expanding sample that only incorporates information up to year $t - 1$. The predicted failure rate is based on the model in column (4) of [Table 1](#) estimated with a linear probability model. Appendix [Table B.16](#) shows the results from using alternative variables and logit estimation. Predicted probabilities are constructed using the first 10 years of the sample as training data. Newey-West standard errors in parentheses with truncation parameter $S = 1.3T^{1/2}$ following Lazarus et al. (2018). *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

[Figure 9](#) plots the realized aggregate failure rate against the out-of-sample predicted aggregate failure rate, $\bar{p}_{t|t-1}$. [Table 3](#) presents estimates of the corresponding time-series regression:

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

There is strong out-of-sample predictability of aggregate bank failures based on past fundamentals. The R^2 for the full sample is 40%. Using richer period-specific models

Figure 9: Fundamentals Predict Aggregate Waves of Bank Failures



Notes: This figure plots the realized aggregate failure rate against the predicted aggregate failure rate, $\bar{p}_{t|t-1}$. The predicted aggregate failure rate for year t is constructed using only information up to year $t - 1$, so the prediction is pseudo out-of-sample using an initial training sample of ten years. The predictions for each sample period are based on the linear probability model in column (4) of Table 1. Table 3 reports the regression version of this figure for the full sample and by era. Negative predicted probabilities are possible due to the use of a linear probability model. Figure B.9 shows the results using logit estimation and with richer period-specific models.

implies an R^2 of 59% (see Table B.16). Deteriorating fundamentals matter not only for individual bank failures; they are also key to understanding widespread bank failures during major banking crises in the U.S. Banking crises are thus, to a significant extent, baked into weak fundamentals, rather than fully unexpected jumps to bad equilibria. This evidence reinforces existing evidence using aggregate data that banking crises are predictable based on variables that forecast subsequent bank losses, such as business failures (Gorton, 1988), credit and asset price growth (e.g., Schularick and Taylor, 2012; Greenwood et al., 2022; Müller and Verner, 2023), and declining bank equity prices (Baron

et al., 2021).

The predicted failure rate is similar in magnitude to the actual failure rate in many years. However, it generally underpredicts the actual failure rate during the Great Depression, consistent with potential excess failures during this major crisis. The estimated slope $\hat{\beta}$ in Table 3 is larger than one in the full sample and in the pre-1934 sample.¹⁹ Interestingly, the coefficient estimate is not significantly different from one in the modern sample (column 3) or when we exclude the Great Depression (column 4). Excess failures are thus mainly driven by the Great Depression, which featured record bank failures from 1930 to 1933.²⁰

The predictability of the aggregate failure rate is especially high in the modern sample. The estimated coefficient in column (3) of Table 3 is close to unity, the constant is close to zero, and the R^2 is 81%. This is likely partly due to improvements in the accounting data, which more quickly reflect bank losses. It may also reflect a change in the nature of bank failures. In the post-FDIC era, the timing of failure is partly determined by government supervisors, since deposit insurance can blunt market forces that would force a bank failure (Walter, 2004; Correia et al., 2025). Therefore, modern bank failures occur later in crises. For example, during the 2008 financial crisis, the highest rate of failures occurred in 2010, followed by 2011 and 2009.²¹ In contrast, in the historical sample, the timing of failure was determined by market forces, such as a run or bank owners seeking to limit

¹⁹Table B.16 show that the estimated slope is larger than one in simpler models with fewer predictors but close to one using richer period-specific models.

²⁰While there are excess failures in the main Depression years 1930 through 1933, our model overpredicts failure in 1934 and 1935. While the over-prediction in 1935 may be directly linked to government interventions and an increased safety net that suppresses failure, the over-prediction in 1934 is in part also related to the timing of the Banking Holiday of 1933 and the timing of the subsequent appointment of receivers (Jaremski et al., 2023). In particular, many banks that suspended in early 1933 reported their last call report in 1932 but the receiver was only formally appointed in 1934, see also Figure A.3. This implies that our model that predicts failure one year ahead is subject to a mechanical sample selection, as some banks that fail in 1934 are dropped due to the lack of financial statements in 1933.

Moreover, there is less evidence of excess failures for other major episodes, such as the panics of the National Banking Era (with the exception of 1893), the Savings and Loan Crisis of the 1980s, and the 2008 Global Financial Crisis.

²¹During the Savings and Loan Crisis of the 1980s, regulatory forbearance significantly delayed failure. Since Prompt Corrective Action was introduced in 1991, a critically undercapitalized bank must be closed or raise new capital within 90 days, accelerating failure for troubled banks.

their losses.

8 Recovery Rates and Asset Quality in Failure

Thus far, we have established that bank failures—including failures involving runs—are strongly connected to weak bank fundamentals. This evidence casts doubt on the role of non-fundamental runs in explaining most bank failures and crises. In this section, we study recovery rates on assets held by failing banks at failure. Under certain assumptions, asset recovery rates allow us to shed additional light on the relative importance of bank runs and insolvency in explaining bank failures.

8.1 Recovery Rates and Asset Quality

[Table 4](#) reports the recovery rate on assets in bank receiverships for the 1863-1934 sample. We define the recovery rate, R , as the ratio of the cash the receiver collected to the book value of total assets available to the receiver. Total assets are defined as assets at suspension and assets received after suspension. Recovery rates on assets are low in the pre-FDIC sample, averaging 52%.²² In 43% of failures, recovery rates are below 50%. Another 49% have recovery rates between 50% and 75%. Only 8% of failed banks have recovery rates above 75%.

What explains these low recovery rates? We first study the OCC's assessments of asset quality made immediately upon a bank's closure. As part of the initial examination process during receivership, the OCC divided the book value of assets into three categories: *Estimated Good*, *Estimated Doubtful*, and *Estimated Worthless*. [Table 5](#) provides statistics on these assessments for all failures in the 1863-1934 sample. On average, the OCC estimated 36% of assets to be good, 47% to be doubtful, and 18% to be worthless.

²²The average recovery rate is even lower when excluding the failures that occurred after the banking holiday in the Great Depression. Bank failures during the banking holiday were the product of a government decision, which led to the closure of some healthier banks that likely had higher quality assets (Jaremski et al., 2023). [Figure B.11](#) plots the average recovery rate over time.

Table 4: Asset Recovery Rates in Failure, 1863-1934

Era	Recovery Rate, R						N
	Average	Share of failures with recovery rate within...					
		<25%	[25%-50%)	[50%-75%)	[75%-95%)	$\geq 95\%$	
1863-1913 (NB Era)	0.45	0.15	0.46	0.34	0.05	0.01	533
1914-1918 (Early Fed)	0.48	0.06	0.49	0.41	0.02	0.01	732
1929-1933 (Depr., pre-Holiday)	0.50	0.07	0.39	0.52	0.02	0.01	1031
1933-1934 (Depr., post-Holiday)	0.65	0.01	0.09	0.69	0.21	0.00	605
All	0.52	0.07	0.36	0.49	0.07	0.01	2901

Notes: This table reports asset recovery rates for failed banks. The sample covers failed national banks from 1863 to 1934. Data are collected from the OCC's annual report to Congress; tables on "National banks in charge of receivers" (various years). The recovery rate on assets is the total collected funds in receivership relative to the sum of total assets held at suspension and collected after suspension. This represents the share of assets that the receiver was ultimately able to recover to compensate claimholders. Note that the receiver also collected funds from shareholders due to double-liability, which increased the overall amount of available funds to distribute to debt holders. [Figure B.11](#) in the appendix plots the average recovery rate by year.

Thus, receivers on average assessed 65% of assets as either "doubtful" or "worthless," indicating a pessimistic view of failed banks' asset quality at the time of bank failure.

The assessed shares of good, doubtful, and worthless assets are strongly related to actual recovery rates. Column (1) in [Table 6](#) reports a regression of the realized recovery rate on the initial assessment of asset quality. It shows that each dollar of good, doubtful, and worthless assets predicts a recovery rate of \$0.89, \$0.54, and \$0.08, respectively, with an R^2 of 94%. While the OCC assessments may contain biases, this indicates that they provide useful information about asset quality. Taken together, the low assessed asset quality and low recovery rate on failed banks' asset holdings suggest that unrealized losses relative to the book value of assets were likely an important determinant of failure.²³

[Table 6](#) further shows that recovery rates are related to several other bank-level proxies

²³James (1991) studies 412 bank failures between 1985 and 1988. He finds that asset losses averaged 30% for failing banks. James (1991) argues that a significant portion of these losses reflect past unrealized losses, rather than liquidation discounts. Focusing on bank failures between 1986-2007, Bennett and Unal (2015) find that the average loss amounted to 33.2% of total assets. Further, Granja et al. (2017) show that in the aftermath of the GFC, the average FDIC loss on a failed bank was around 28% of assets, with a substantial part of these losses resulting from frictions in the market for failed banks. Our evidence is broadly consistent with these papers, although we find that the recovery rates were lower in the pre-FDIC sample.

Table 5: OCC Assessment of Asset Quality in Failure, 1863-1934

Era	Assets at suspension			N
	Estimated Good	Estimated Doubtful	Estimated Worthless	
1863-1913 (NB Era)	0.35	0.40	0.26	533
1914-1918 (Early Fed)	0.35	0.40	0.26	732
1929-1933 (Depr., pre-Holiday)	0.31	0.56	0.15	1031
1933-1934 (Depr., post-Holiday)	0.46	0.47	0.08	605
All	0.36	0.47	0.18	2901

Notes: This table reports estimates of the share of good, doubtful, and worthless assets at the time of suspension. The sample covers failed national banks from 1863 to 1934. Data are collected from the OCC's annual report to Congress; tables on "National banks in charge of receivers," (various years). Good, doubtful, and worthless assets at suspension are normalized by total assets at suspension.

of asset quality. We measure these proxies in the last call report before failure. The recovery rate is lower in smaller banks, in line with less well-diversified banks suffering larger losses in failure. It is also lower in less well-capitalized banks, suggesting that poor asset performance depresses both pre-failure capitalization and recovery in failure. Similarly, it is lower in banks that report a higher share of non-performing loans and a higher loans to liquid asset ratio before failure, indicating that banks with more bad loans tend to experience larger asset losses in failure. Finally, a larger boom-bust cycle before failure is associated with a lower recovery rate in failure. In particular, the recovery rate is lower for banks that have rapid asset growth from ten to seven years before failure, consistent with rapid asset growth going hand-in-hand with more risk at the margin. It is also lower for banks that have the slowest growth in the last three years before failure.

The low recovery rate on assets in the pre-FDIC sample implies substantial loss rates for depositors in this period compared to the modern period. Appendix [Table B.18](#) presents estimates on the loss rates for uninsured depositors for bank failures in the pre- and post-FDIC samples. In the pre-FDIC sample, 81% of failures involved losses for depositors, and the average unconditional depositor recovery rate was 66%. Moreover, depositors often experienced a substantial delay before receiving their funds. On average,

the depositor recovery rate in the initial year is only about 35% (see [Figure B.10](#)). In contrast, in the 1992-2022 sample, only 20% of failures involved losses for uninsured depositors, and the average unconditional loss rate is 6%.

8.2 The Share of Fundamentally Insolvent Banks

As we outlined in [Section 2](#), a central yet challenging question is whether runs commonly cause the failure of weak but solvent banks or whether runs mainly trigger the failure of *ex ante* insolvent banks. To address this question, we spell out a simple framework that we take to the granular data on pre-FDIC bank receiverships.

Suppose a failed bank has book assets A and debt D , where debt includes both deposits and non-deposit borrowing. Further, assume the bank has unrealized losses on assets before entering failure of λ and incurs additional losses in receivership of ρ . $\rho > 0$ captures the idea that bank closure itself may cause additional losses. These additional losses can result from a wedge between the value of the assets in the bank and the value for the next best user. For instance, the value of bank assets can be tied to the human capital of the manager (e.g., Diamond, 1984; Hart and Moore, 1994; Diamond and Rajan, 2001), or the receiver may be inefficient in managing a failed bank's assets. The recovery rate we observe in receivership, R , is thus a combination of unrealized asset losses from before failure and losses in receivership: $R = (1 - \lambda)(1 - \rho)$. Further, let v be the franchise value as a fraction of current book assets.

The bank is insolvent irrespective of the run if the value of its assets and franchise falls short of its debt:

$$(1 - \lambda)(1 + v)A = \frac{R}{1 - \rho}(1 + v)A < D.$$

If this inequality does not hold, the failed bank was solvent in the absence of the run. Let

Table 6: Predictors of Asset Recovery Rate in Receivership

Dependent variable	Recovery Rate, R				
	(1)	(2)	(3)	(4)	(5)
<i>Good</i> at suspension	0.89*** (0.01)				
<i>Doubtful</i> at suspension	0.54*** (0.01)				
<i>Worthless</i> at suspension	0.08*** (0.02)				
Size (log(assets))		2.93*** (0.29)			
Surplus/equity			15.49*** (1.77)		
Noncore funding/assets			-2.50 (3.27)		
Loans/assets			-28.62*** (2.12)		
NPL/loans				-25.38*** (9.52)	
Q1 of loan growth (t-10,t-3)					-1.38 (1.15)
Q2 of loan growth (t-10,t-3)					-0.45 (1.17)
Q4 of loan growth (t-10,t-3)					-0.73 (1.18)
Q5 of loan growth (t-10,t-3)					-3.44*** (1.14)
Q1 of loan growth (t-3, t-1)					-7.34*** (1.10)
Q2 of loan growth (t-3, t-1)					-3.37*** (1.20)
Q4 of loan growth (t-3, t-1)					-2.10 (1.34)
Q5 of loan growth (t-3, t-1)					-0.43 (1.36)
N	2682	2710	2708	418	1986
R^2	0.936	0.035	0.098	0.017	0.038

Notes: This table reports results from estimating regressions of the following form: $R_b = \alpha + \beta X_b + \epsilon_b$. The sample is receiverships in 1863-1934. The recovery rate, R_b , is calculated as the ratio of the total funds collected in receivership over total assets held at suspension and additional assets received after suspension. X_b is a set of bank characteristics observed before or in receivership, including characteristics such as the share of assets assessed as *good*, *doubtful* or *worthless* by the receiver at the onset of the receivership and balance sheet characteristics from before receivership. NPL is proxied by Other Real Estate Owned, available for the 1889-1904 subsample. We also include indicators for the quintile of the loan growth distribution (across all banks within the same calendar year) in both the boom phase (10 to 3 years before failure) and the bust phase (3 years before failure to last call before failure). The regression in column (1) is estimated without a constant. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

$\ell = D/A$ denote the bank's leverage. The insolvency condition can be written as

$$\frac{1+v}{1-\rho} < \frac{\ell}{R}. \quad (3)$$

This condition captures the intuition that, all else being equal, loss rates $(1 - R)$ and leverage (ℓ) cannot be too high for a run to cause the failure of an *ex ante* solvent bank. If the recovery rate R is high relative to leverage ℓ , it would be plausible that the run destroyed the bank's franchise value, but the bank was solvent absent the run. In contrast, very low recovery rates combined with high leverage would suggest that the bank was insolvent, irrespective of whether a run took place or not.

Our newly digitized micro-data on bank receivership allows us to estimate ℓ and R for each bank. Specifically, we calculate ℓ as the amount of claims proved by depositors plus secured and preferred liabilities paid at failure, relative to total assets (see [Appendix C.2](#) for details). As above, we calculate the recovery rate R as total collections from assets relative to total assets.

The loss in receivership, ρ , and franchise value, v , on the other hand, are not directly observable. The loss in receivership ρ is likely to be positive if the bank manager is better than the receiver in collecting on bank assets. At the same time, unlike non-financial firms, which hold mostly assets that are considerably more valuable inside a firm than outside a firm, banks largely hold assets that can be separated and repossessed, such as securities and loans. Moreover, OCC receivers were generally considered to be experts in collecting on failed banks' assets, could not sell assets without the approval of the Comptroller and a court order, and were charged with liquidating assets in an orderly fashion (Upham and Lamke, 1934). OCC receivers often held assets for several years in order to avoid fire sales. The median receivership lasts for six years (see [Table B.21](#)). Therefore, the loss in receivership is not necessarily large. Banks enter failure with very low-quality assets, which suggests managers of these failed banks may not have been highly skilled at screening and collecting from borrowers.

There is also a range of plausible values for the franchise value, v . Franchise value varies across banks and over time based on technology, regulation, the competitive environment, and market conditions (e.g., Keeley, 1990). Estimates of franchise value

based on Tobin’s q or valuations of bank income and expenses range from 0% to 20% (e.g., Demsetz et al., 1996; Ma and Scheinkman, 2020; Hirtle and Plosser, 2024; DeMarzo et al., 2024). These estimates are, of course, based on specific equilibria and may not apply to failing banks. Indeed, we view these estimates as likely upper bounds for failing banks, given that we find these banks generally undergo a deteriorating business model before failure.

Table 7: *Share of Fundamentally Insolvent Banks by ρ and v , 1863-1934*

ρ	$v = 0$	$v = 2.5\%$	$v = 5\%$	$v = 7.5\%$	$v = 10\%$	$v = 15\%$	$v = 20\%$
0%	0.81	0.77	0.75	0.72	0.69	0.62	0.56
5%	0.74	0.71	0.68	0.65	0.62	0.55	0.49
10%	0.67	0.64	0.60	0.57	0.54	0.48	0.43
20%	0.50	0.48	0.45	0.42	0.40	0.36	0.31

Notes: This table reports the share of failed banks that are fundamentally insolvent, calculated as

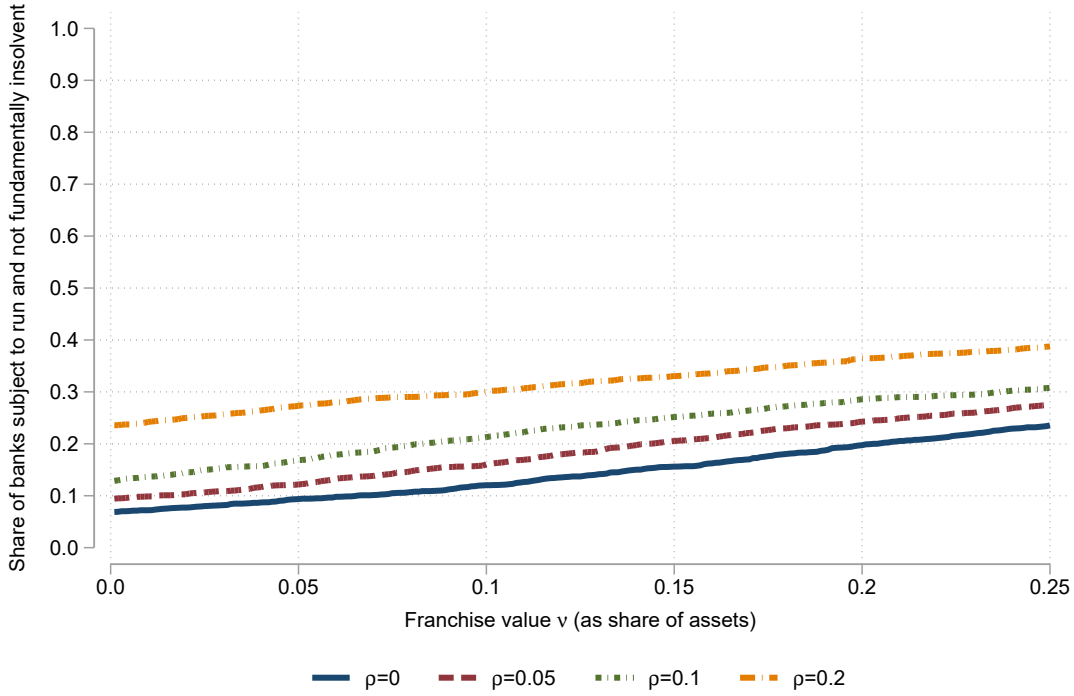
$$\frac{1}{N} \sum_b \mathbb{I} \left[\frac{1+v}{1-\rho} < \frac{\ell_b}{R_b} \right].$$

ρ and v are the unobservable loss in receivership and the franchise value as a fraction of current book assets, respectively. ℓ_b and R_b are the observable ratio of debt to assets and recovery rate on assets, respectively. The calculations are based on the sample of national banks placed in charge of receivers from 1863 through 1934.

[Table 7](#) presents the share of fundamentally insolvent banks, defined as the share of banks for which condition (3) holds. Given the range of possible values of the receivership loss rate and franchise value, we report the shares for various combinations of ρ and v . When $\rho = v = 0$, the framework implies that the share of fundamentally insolvent banks is 81%. Assuming a $\rho = 0.1$ and $v = 0.05$ implies 60% of failed banks were fundamentally insolvent. Interestingly, when we separately examine failures by those with and without large deposit outflows immediately before failure, we find that a greater share of banks that failed with a run were likely to be insolvent (see [Table B.19](#)), consistent with runs happening in the weakest banks.

What is the share of fundamentally solvent banks that could have failed because of a run? To answer this question, we make use of two testable implications of bank run

Figure 10: Share of Banks Subject to Run that Were Not Fundamentally Insolvent



Notes: This figure plots the share of banks that are subject to a deposit outflow of more than 7.5% between their last call report and suspension and that are not fundamentally insolvent, defined as

$$\frac{1}{N} \sum_b \mathbb{I} \left[\frac{1+v}{1-\rho} \geq \frac{\ell_b}{R_b} \right] \times Run_b.$$

ρ is the loss in receivership, and v is the franchise value as a fraction of current book assets, ℓ is the ratio of debt to assets, R is the recovery rate on assets, and Run_b is an indicator variable that equals one for banks that experienced a decline in deposits between the last call report and failure of greater than 7.5%. We restrict the sample to national banks placed in charge of receivers between 1880 and 1934 for which “deposits at suspension” is reported by the OCC.

theories, discussed in [Section 2](#). First, for a bank run to represent a plausible cause of failure, a failing bank needs to experience significant deposit outflows before failure. Second, the failed bank should not have been fundamentally insolvent.

[Figure 10](#) presents the share of failed banks subject to a run that were *not* fundamentally insolvent, i.e., $\frac{1+v}{1-\rho} \geq \frac{\ell_b}{R_b}$. As before, we define a bank as being subject to a run if it loses more than 7.5% of its deposits immediately before failure. We report this share for various values of ρ and v .

For $\rho = v = 0$, less than 8% of bank failures could have plausibly been caused by a

run on an *ex ante* solvent bank. In the language of Goldstein and Pauzner (2005) from [Section 2](#), less than 8% of banks fail with $\theta \in (\underline{\theta}, \theta^*)$. The higher the assumed potential value of the bank absent a run, the greater is the share of banks that could have failed because of the run. With $\rho = v = 0.05$, this share rises to 13%. For $\rho = v = 0.1$, which would imply that value destruction because of failure itself exceeds 20%, the share is 22%. While the exact share of fundamentally solvent banks that failed because of a run depends on assumptions about the potential value destroyed by the run, the calculations summarized in [Figure 10](#) suggest that runs on otherwise solvent banks account for a modest, although not negligible, share of failures before the introduction of deposit insurance. Put differently, even when assuming that bank failure induced large value reduction, the majority of pre-FDIC failures involved either fundamentally insolvent banks or banks that were not subject to large deposit outflows.

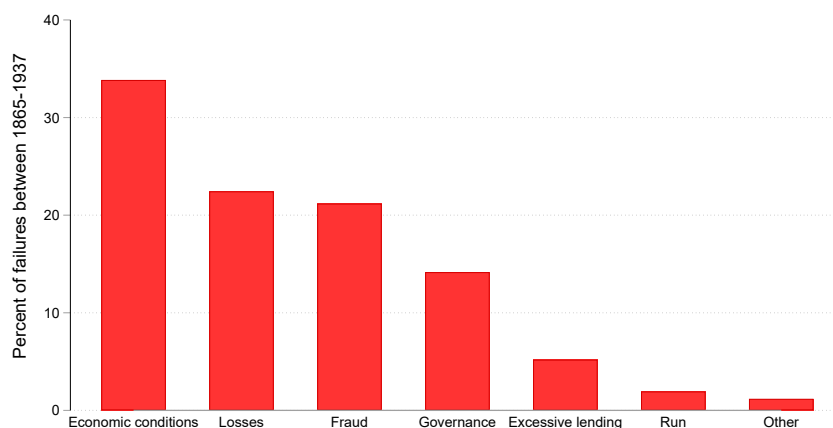
8.3 Cause of Failure Assigned by OCC

Our empirical evidence suggests that asset losses that drove banks to insolvency were an important driver of pre-FDIC bank failures. While runs were common in failing banks, in most cases, these runs were likely the trigger of failure of *ex ante* insolvent banks, rather than the original cause of failure for otherwise solvent banks.

How does this interpretation align with contemporary views of pre-FDIC failures? As a final piece of evidence, [Figure 11](#) reports the distribution of the “cause of failure” provided by the OCC for most failures that occurred between 1863 and 1937. We summarize the causes of failure assigned by the OCC into seven broad categories: economic conditions, excessive lending, losses, fraud, governance issues, run, and other factors.²⁴ While the OCC classification may contain errors, it nevertheless provides insight into what

²⁴Systematic classification of the cause of bank failures by the OCC is essentially complete for 1863-1928, but it is only partial for failures that occurred during 1929-1931 and is not available for banks that failed in 1932 or 1933. See [Appendix C.2](#) for details on the sample coverage and how we classify the detailed causes of failure into broad categories.

Figure 11: Causes of Bank Failures as Classified by the OCC, 1863-1937



Notes: Causes of failure are as classified by the OCC in the tables of national banks in charge of receivers from the OCC annual report to Congress for various years. We categorize the detailed list of failure reasons as described in [Appendix C.2](#). The classification of the causes of bank failures by the OCC is essentially complete for failures from 1863-1928, partially complete for failures from 1929-1931 and 1934-1937, and entirely missing for failures in 1932 and 1933 (see [Figure C.5](#)).

examiners on the ground saw as the main cause of failure for each bank.

[Figure 11](#) shows that the most common cause of failure provided by the OCC is “economic conditions.” This category includes failures attributed to deflation, crop loss, and a local financial depression. The second most common category is “losses.” The third most common category is “fraud,” which also often occurs in response to losses. Other common causes are “governance issues” and “excessive lending,” which refers to a bank with excessive exposure to one counterparty. The most common causes of failure are thus related to deteriorating asset quality and poor fundamentals.

Bank runs, in contrast, account for less than 2% of all failures according to the OCC, despite the preponderance of failures that involved large deposit outflows in this period. “Run” covers instances where the bank was closed by a run, heavy withdrawals, and a lack of public confidence, as well as cases where the bank was closed by directors in anticipation of a run or due to rumors of a run. Contemporary observers rarely saw runs as the principal cause of failure (see also Board of Governors of the Federal Reserve System, 1936; Calomiris and Gorton, 1991).

9 Discussion

This paper studies failing banks using novel data spanning 1863-2024 on more than 37,000 banks in the United States. Throughout the sample, bank failures are preceded by gradually deteriorating solvency and increasing reliance on expensive noncore funding. Worsening fundamentals are often preceded by rapid lending growth and driven by a realization of credit risk. As a result, bank failures are highly predictable. Failures with bank runs, a common phenomenon before deposit insurance, are as predictable as failures without runs. Aggregate waves of bank failures are also predictable by weak bank fundamentals. Most pre-FDIC bank failures featured poor asset quality, with an average asset recovery rate of 52%.

Our findings have important implications for theories of bank failures and banking crises. We generalize the notion that weak bank fundamentals are a necessary condition for failure and show that non-fundamental runs on healthy banks are a rare cause of failure, even before deposit insurance. More than that, we find that most pre-FDIC bank failures involved *ex ante* insolvent banks. Runs on weak but solvent banks likely account for only a modest share of failures, barring strong assumptions about the value destruction of receiverships.

One explanation for why runs on solvent banks are an uncommon cause of failure is that private sector arrangements may often resolve liquidity shortages, even in the absence of government interventions. For instance, to the extent that interbank market participants can distinguish whether distress results from liquidity or solvency concerns, interbank lending can provide insurance against temporary liquidity pressures (Blickle et al., 2024). For the historical U.S. banking system, solvent banks facing runs could suspend convertibility until they could secure additional liquidity, often through arrangements such as clearinghouses, rather than engage in mutually destructive asset fire sales (Gorton, 1985a,b). Therefore, while runs on healthy banks did occur, these generally did not trigger failure.

At the same time, our evidence emphasizes that runs on failing banks were frequent before the adoption of deposit insurance. Runs were likely an important mechanism for closing insolvent banks, determining the timing of many failures. Absent supervisory intervention, many pre-FDIC bank failures can be thought of as requiring a double trigger of both insolvency and a bank run that made a bank illiquid. Furthermore, our findings on the dynamics in failing banks point to the importance of a feedback loop in which solvency deterioration leads to increased reliance on expensive funding that further erodes solvency. These “slow run” dynamics are not captured by most bank run models. Overall, our findings suggest that the *solvency view* goes a long way to understanding the primary cause of bank failures, but the runnable nature of bank liabilities, central to the *bank runs view*, can be important for understanding when and how banks fail.

Our evidence offers a nuanced perspective on the wide-ranging views of the role of depositor discipline (Calomiris and Kahn, 1991; Diamond and Rajan, 2001). Before deposit insurance, failures involving large deposit outflows were common. This suggests that depositor behavior was often important for triggering failure. In contrast, in the modern era, deposit outflows are small, and insured deposits even flow into failing banks. This indicates important changes in the extent to which depositors discipline banks due to changes in regulation, as also suggested by Martin et al. (2023). At the same time, large depositor losses and the significant predictability of bank failures also suggest that depositors are slow to react to information about bank fundamentals, potentially consistent with theories of inattention. Hence, depositor discipline before deposit insurance was imperfect.

Our results also speak to theories of banking crises based on asymmetric information. An older literature models bank runs as potentially arising from asymmetric information in which depositors may react to signals of poor fundamentals or to changes in beliefs triggered by noisy signals such as rumors (see, e.g., Gorton, 1988; Chari and Jagannathan, 1988). In this view, even solvent banks can fail if depositors, lacking full information,

panic and withdraw funds based on rumors. Our evidence that most banks that fail have weak fundamentals and are insolvent, as well as the predictability of failures, suggests that runs triggered by asymmetric information are unlikely to result in failure but may be resolved through other mechanisms.

Our results further inform research on the “information view” of financial crises (Dang et al., 2017, 2020). In this view, banking crises happen when creditors revise their assessment of bank assets after receiving signals about the state of the banking system or the economy. These revisions, in turn, cause liabilities to become more fragile, as counterparties shorten maturities and demand collateral. Sufficiently bad signals trigger system-wide runs out of bank debt and into cash. Consistent with the information view, we find that bank failures and runs are preceded by losses that lead banks to have more fragile funding. However, our findings of significant predictability of aggregate waves of failure based on weak fundamentals suggest that information or behavioral frictions in belief formation may also be key to understanding the nature of financial crises.

Our findings emphasizing the central role of fundamentals and bank solvency have important policy implications. The predictability of bank failures implies a role for *ex ante* interventions to prevent bank failures or mitigate their damage (Gennaioli and Shleifer, 2018). The fact that bank failures are predictable supports the active use of prompt corrective action measures, such as limiting dividend payouts and the use of non-core funding for poorly capitalized banks. More generally, our findings emphasize the importance of requiring financial intermediaries to be well-capitalized. Our findings also imply that *ex post* interventions during a crisis must address fundamental solvency issues. When a crisis is driven by poor fundamentals, liquidity support without addressing insolvency is insufficient for mitigating the adverse consequences of banking sector distress, as argued by recent empirical and theoretical work (Baron et al., 2024; Amador and Bianchi, 2024).

Finally, our conclusions are subject to important caveats. Our empirical analysis

focuses on bank failures. We do not study bank runs that do not ultimately result in bank failure. Panic-based runs could force otherwise healthy banks or banking systems to suspend convertibility of deposits into cash. Such suspensions can cause uncertainty and disrupt the payments system, with adverse real economic effects, even if no bank failures follow (Sprague, 1910). In short, while we emphasize the important role of fundamental insolvency for bank failures, our paper should not be read as saying that runs and panics do not matter for understanding the severity of banking crises.

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Failing Banks

Online Appendix

Sergio Correia, Stephan Luck, and Emil Verner*

June 5, 2025

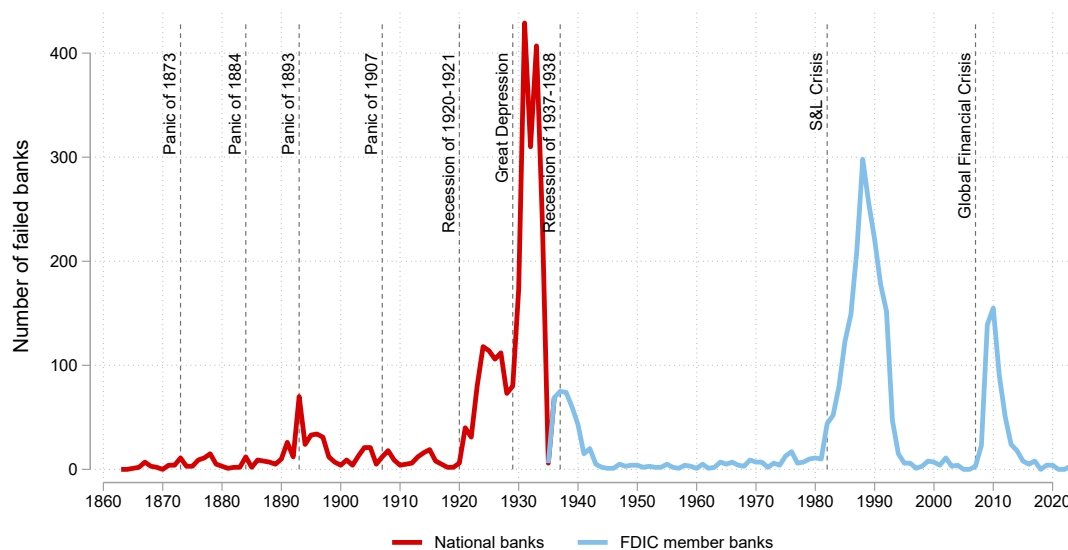
- Appendix A: Evolution of the U.S. Banking System and Bank Failures
- Appendix B: Additional Tables and Figures
- Appendix C: Data Appendix

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A 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](#) in the paper shows the failure rate throughout our sample. [Figure A.1](#) plots the number of failures. [Table A.1](#) summarizes the key institutional and regulatory features by era.

Figure A.1: *Failing Banks: 1863-2024*



Notes: This figure plots the number of failed banks by year. Vertical lines indicate selected major banking crises and economic downturns. The red line plots the number of failing national banks, defined as national banks placed into receivership. The blue line plots the number 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.

National Banking 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. It was preceded by what is now referred to as the Free Banking Era, during which banks could charter under state laws after fulfilling a simple set of regulatory requirements (see, e.g. Rolnick and Weber, 1983). Since the United States did not have a central bank for most of the nineteenth century, these state-chartered banks were the main issuers of notes in circulation. To be able to issue bank notes, banks had to cover their note issuance with purchases of state-issued government bonds. This changed during the Civil War, when the federal government needed to finance the war. To increase demand for federal government bonds, Congress passed two laws (the National Currency Act in 1863 and the National Banking Act in 1864) that allowed banks to be chartered under federal law—thus the name: national banks. Like state banks before them, national banks were allowed to issue bank notes when backed by government bonds. Currency issued by state banks was taxed at a high rate that encouraged banks to adopt national charters and purchase federal government bonds. The National Banking

Act also established a regulatory and supervisory authority, the Office of the Comptroller of the Currency (OCC). The OCC published national bank balance sheets every year in an annual report to Congress, as discussed in the data section.

Other than issuing currency, national banks operated very much as banks do today, by taking deposits and making loans. However, there was very little government interference. For instance, there was no insurance for deposits. Moreover, as there was no central bank, there was also no lender of last resort to help banks in a crisis. The Treasury performed quasi-central bank operations toward the end of the National Banking Era, but the interventions were small (Friedman and Schwartz, 1963). Thus, in this period, we can be reasonably confident that bank behavior was not driven by the anticipation of government support. Moreover, national banks were restricted to operating as unit banks, which meant that each bank could only operate a single branch serving a single location. Finally, capital regulation during the National Banking Era did not restrict the leverage ratio but reflected entry barriers (Carlson et al., 2022). At the founding of a bank, the bank charter would determine the dollar-amount of capital paid in to the bank with a minimum amount determined by the population of the bank's location. Thereafter, banks were largely able to choose their leverage freely subject to market conditions, though banks did face restrictions on dividend payouts based on their surplus. National banks were subject to double liability. In the event of failure, a receiver would levy an additional assessment on the bank shareholders' equal to the par value of subscribed capital to cover losses to depositors (Grossman, 2010). National banks were subject to double liability until 1937. National banks also faced portfolio restrictions limiting their capacity to lend against real estate collateral (White, 1983).

The National Banking Era witnessed a series of banking crises. The banking crisis chronology of Baron et al. (2021) records banking crises featuring widespread bank failures and panic-runs in 1873, 1884, 1890, 1893, and 1907. For the National Banking Era, [Figure 1](#) shows that the rate of failure of national banks was highest around the Panic of 1893.

While there was limited government intervention in response to banking panics and crises, banks responded to funding pressures and runs through various private sector arrangements. In many cases, banks would suspend convertibility into cash, either by fully or partially restricting withdrawals. Suspension was usually undertaken by a group of banks through local clearinghouse associations. In response to panics, clearinghouses would also halt the publication of individual bank balance sheets and instead publish an aggregate balance sheet for all members (Gorton, 1985b). Further, clearinghouses would act as quasi-central banks by issuing loan certificates, a joint liability of all members, which banks could use in the clearing process. In certain panics (1893 and 1907), clearinghouses issued loan certificates directly to the public, expanding the money supply. Clearinghouses would also audit banks that were in distress to evaluate their solvency, and insolvent banks were expelled from the clearinghouse. Clearinghouse associations operating at the city level provided emergency liquidity to member banks during panics (Jaremski, 2018). The New York Clearinghouse (NYCH) lent to troubled banks throughout the country in certain cases (Gorton, 1985b). The NYCH performed these functions effectively in the Panic of 1873, but not in later panics, as member banks struggled to internalize the collective interest of such interventions (Wicker, 1996).

Table A.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 Leverage ratio in 1985	Local branching
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, some states had already implemented deposit insurance schemes for state-chartered banks 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.

Early Federal Reserve & Great Depression The recurring financial crises of the National Banking Era led to the creation of a central bank through the Federal Reserve Act of 1913. The Federal Reserve could serve as a lender of last resort and had the responsibility to supervise member banks (see, e.g., Carlson, 2025).

The McFadden Act 1927 liberalized restrictions on national banks. Before the Act, national banks were prohibited from opening branches. The Act allowed national banks to branch in states where state banks were permitted to branch, a step toward liberalization of geographic restrictions (see, e.g., Rajan and Ramcharan, 2016). The McFadden Act also liberalized rules for Federal Reserve member banks to lend against real estate and expanded lending limits to single borrowers. Moreover, the McFadden act rechartered the Federal Reserve into perpetuity, removing the risk that the charter would be revoked, as had occurred with the First and Second Banks of the United States.

The 1920s witnessed a rise in banking failures. Failures were concentrated in agricultural states and primarily affected small, rural banks. The rise in bank failures was driven by a sharp decline in agriculture and land prices in agrarian states, as well as rising urbanization that weakened the position of rural banks (Friedman and Schwartz, 1963). [Figure 1](#) shows that the failure rate of national banks reached a new high in the 1920s, even before the Great Depression.

The Great Depression further exacerbated distress among banks, and several scholars have argued that the banking crisis, in turn, contributed to the severity of the downturn (e.g., Friedman and Schwartz, 1963; Bernanke, 1983). The wave of bank failures prompted a decades-long debate about whether failures were mainly liquidity-based due to depositor runs (Friedman and Schwartz, 1963) or driven by fundamentals such as rising losses (Calomiris and Mason, 2003). Richardson and Troost (2009) exploit that the Atlanta and St. Louis Federal Reserve banks followed different lender of last resort policies and find that Fed liquidity reduced bank failures and boosted lending, pointing to a role for

liquidity-based failures. This also highlights that lender of last resort facilities were not uniformly available, even with a central bank, especially as the discount window became stigmatized.

The Great Depression prompted a wave of banking reforms. Deposit insurance was introduced in 1933 and then made permanent in 1934 with the creation of the FDIC. State-level deposit insurance systems had existed before, but these became inoperative by Great Depression (Calomiris and Jaremski, 2019). However, state-level deposit insurance schemes did not apply to national banks. Great Depression banking reform also imposed a range of limits of banking activities (Kroszner and Strahan, 2014). The Glass-Steagall Act prohibited commercial banks from engaging in investment banking activities (corporate bond and equity underwriting). It also imposed limits on interest rates that banks could pay on deposits, known as Regulation Q (Gilbert, 1986).

The Great Depression brought an end to shareholder double liability. The Banking Act of 1933 allowed for the issuance of shares without double liability, and the Banking Act of 1935 allowed national banks to remove double liability from their shares in 1937 (Tufts and Tufts, 2001). Double liability was unpopular among bank shareholders following the high rates of failure during the Depression. It was also seen as ineffective in preventing bank failures and unnecessary with the advent of deposit insurance (Grossman, 2001).

Some notes on the Dual Banking System In our analysis in the main paper, we rely entirely on data on national banks for the period prior to the founding of the FDIC. As noted in the main text, 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.

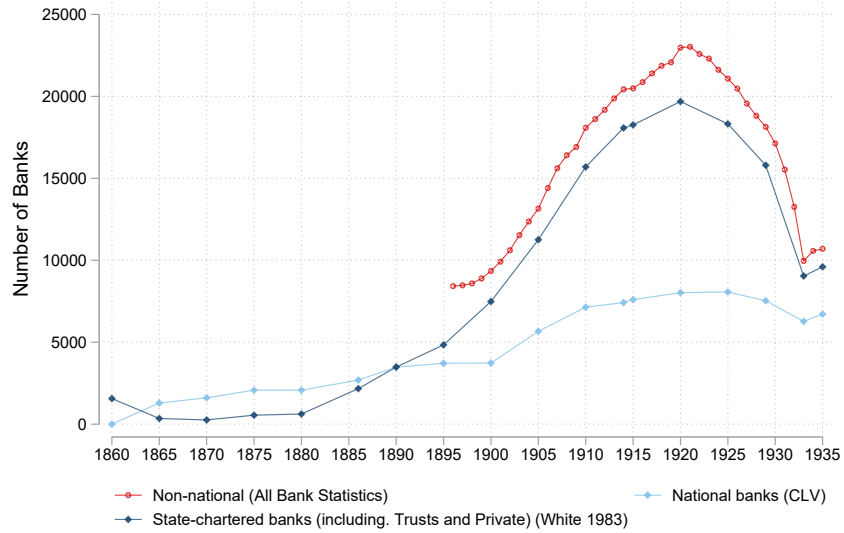
For instance, Figure A.2 plots the number of national banks and state-chartered institutions (panel (a)) and their market share of total banking assets (panel (b)). National banks had a very large market share of the entire banking market ranging of around 80% at the onset of the National Banking Era. This large market share is related to the fact that the National Banking Act imposed a tax on notes issued by state banks, making state bank charters very unattractive. However, starting in the 1880s, the rise of deposits as form of money slowly eroded the note-issuing advantage of national banks. Thus, over time the market share of national banks started to shrink, reaching 45% by the 1930s. More generally, state-chartered institutions tended to be active in smaller markets in which national banks, which faced considerable stricter regulatory requirements, were not viable. Hence, state banks tended to be smaller in size, but there tended to be more state banks than national banks. This naturally implies that national banks tended to have larger, more financially sophisticated depositors than state banks.

While Figure 1 in the main text plots the failure rate (receivership) of national banks, Figure A.3 plots the suspension and receivership rates for national banks and suspension rates for state-chartered institutions. Observe that before 1892, there is no reliable source of state bank suspensions and receivership. After 1892, it became possible to construct a

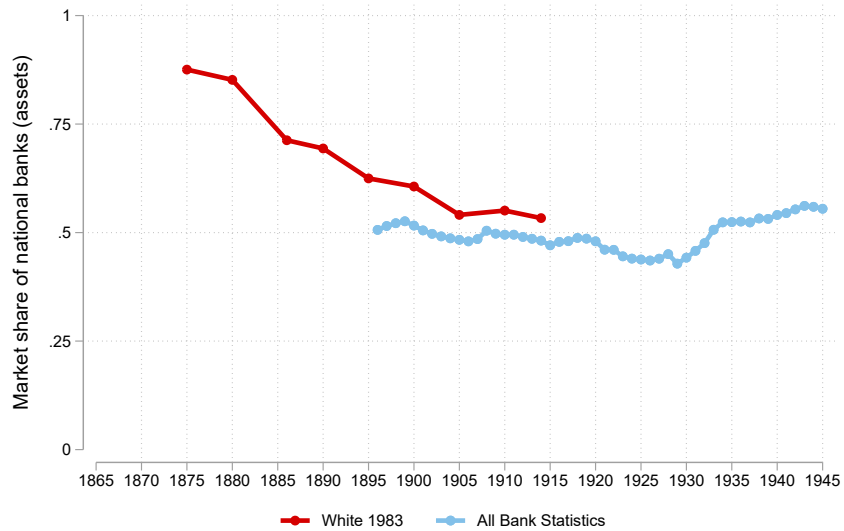
series for both. [Figure A.3](#) shows that failure rates co-moved broadly, with state banks facing slightly higher failure rates than national banks. However, note that the counts of state-chartered institutions changed across sources (differing in the inclusion of trusts, mutual banks, and private institutions), making it *de facto* impossible to construct a consistent time series of failure rates across all bank types. Hence, the levels of failure rates before and after 1920 are not comparable across time.

Figure A.2: Number of Banks by Type and the Market Share of National Banks

(a) Number of banks

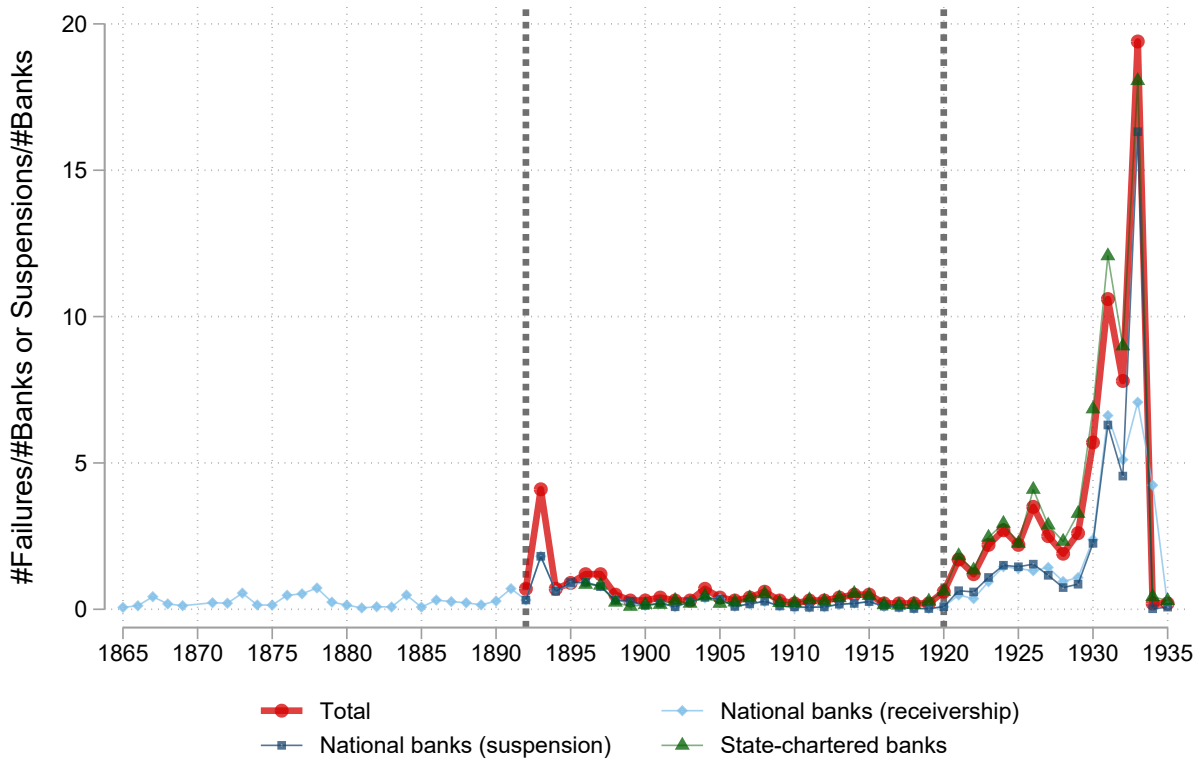


(b) Market share of national banks based on total assets



Notes: Data on state banks, trusts, and private bank are as indicated in the legend either taken from White (1983) and “All Bank Statistics” digitized by Flood (1998). State bank assets are available from 1875 onwards in White (1983); assets of trusts and private bank from 1886 onwards in “All Bank Statistics”. Number of national banks in panel (a) are taken from the sample used in this paper.

Figure A.3: Bank Failures and Suspensions by Bank Type



Notes: This figure combines various sources to construct a rate of bank failure from 1863 through 1935 for national banks, state-chartered banks, and all banks combined. From 1863-1891, we use the U.S. Comptroller of the Currency Annual Report list of failed banks. From 1892-1920, the number of bank suspensions are from Chapter X of the “Historical statistics of the United States, Colonial Times to 1957” (available [here](#)). For 1921-1934, data are the Board of Governor’s from “Bank Suspensions, 1892 - 1935” (available [here](#)). Note that differences in sources between 1864 and 1892, 1892-1920, and 1921-1934 complicate comparisons across time.

Boring Banking We refer to the era from 1959 through 1982 as the “Boring Banking” Era. The term “Boring Banking” is inspired by Paul Krugman, who wrote in the New York Times on April 9, 2009: “Thirty-plus years ago, when I was a graduate student in economics, only the least ambitious of my classmates sought careers in the financial world. Even then, investment banks paid more than teaching or public service - but not that much more, and anyway, everyone knew that banking was, well, boring.” During this era, failure rates were low. Banks’ activities were restricted by the Depression-era regulations. Furthermore, the 1956 Bank Holding Company Act allowed states to restrict entry by out-of-state banks and holding companies, which effectively prohibited interstate banking. There was no explicit capital requirements. Instead, capital regulation was conducted by supervision, and supervision focused not just on capital ratios but on a broader range of quantitative and qualitative factors (Haubrich, 2020).

Rising inflation and interest rates led to outflows of deposits from commercial banks and into money market funds that were not subject to interest rate ceilings. This led to a phasing out of interest rate ceilings on deposits with the 1980 Depository Institutions Deregulation and Monetary Control Act (Kroszner and Strahan, 2014).

Deregulation and Savings & Loan (S&L) Crisis The period of low bank failure rates came to an end in the late 1970s as the number of bank failures started to edge up. Bank failures further increased throughout the 1980s. While the failures in the S&L crisis were highest among thrifts, commercial banks also saw high failure rates during 1980s (see [Figure 1](#)). The S&L crisis is often dated to 1984 based on the failure of Continental Illinois, which represented the largest bank failure in U.S. history at the time. Failures in the 1980s were driven by a combination of high interest rates, the severe recessions over 1980-1982, losses on oil and gas loans, and losses from exposure to the Latin American debt crisis.

In response to rising bank failures and a trend of declining bank capital ratios discussed below, the 1980s witnessed the formal introduction of modern regulatory capital ratios that require a minimum amount of equity finance as a share of total assets. In the early 1980s, both the OCC and the Federal Reserve communicated a simple leverage ratio requirement of 5% equity finance and noted that banks falling short of this cutoff would be considered undercapitalized. Both the Federal Reserve and the OCC published numerical capital ratios in 1981. According to Tarullo (2008), the agencies in effect adopted a minimum requirement of capital-to-assets of 5%. The FDIC only published guidelines on “minimum acceptable levels” of primary capital. The original published requirements excluded the 17 largest banks (those with \$15B or more in assets) but by June 1983, these banks were also included. The International Lending Supervision Act (ILSA) of 1983 then formally required regulatory agencies to explicitly set capital ratios. By 1985, Federal Reserve, OCC, and the FDIC had formalized and published final regulations similar to those of the original 1981 guidelines. Rising inflation and interest rates led to outflows of deposits from commercial banks and into money market funds that were not subject to interest rate ceilings. This also led to a phasing out of interest rate ceilings on deposits with the 1980 Depository Institutions Deregulation and Monetary Control Act (Kroszner and Strahan, 2014).

Following this period of formalizing capital regulation, capital requirements based

on risk-weighted assets also became increasingly popular. In the 1950s, the Federal Reserve developed its Analyzing Bank Capital (ABC) model, which was an early method to construct a capital ratio based on risk-weighted assets. The S&L Crisis also led Congress to pass the FDIC Improvement Act in 1991. A key provision of this Act was the introduction of Prompt Corrective Action (PCA), which requires supervisors avoid exercising forbearance and to take increasingly severe actions when a bank is deemed to be undercapitalized.

At the same time, there was a move toward levelling the international playing field for banks. To this end, the Basel I accord was finalized in 1988 and implemented in the U.S. in 1991. Basel I introduced a minimum capital requirement of 8% based on risk-weighted assets. Risk-weight varied from 0% for supposedly risk-free assets such as cash up to 100% for the most illiquid and risky forms of bank lending such as corporate debt. Further, to address various practical issues around the implementation of Basel I was revised and followed by Basel II in 2007. The Basel II framework left the overall required amount of capital unchanged but allowed for the possibility of banks opting into using their own internal risk models rather than the simple risk weights provided in Basel I. Moreover, Basel II attempted to address issues around off-balance sheet exposures that allowed for an effective circumvention of capital requirements.

Global Financial Crisis and Beyond Finally, the Global Financial Crisis (GFC) initiated additional drastic changes in regulation and supervision of financial institutions. Basel III and the Dodd-Frank Act led to both more stringent and more complicated capital requirements. Capital ratios were increased relative to Basel II and the definition of what constitutes capital was tightened. Capital requirements became differentiated by bank, with the tighter requirements for the largest banks, the Global Systemically Important Banks. Basel III also introduced a capital conservation buffer, limiting bank payouts when capital falls close to the minimum capital ratios, and a counter-cyclical capital buffer (CCyB), which is set at the discretion of the Board of Governors of the Federal Reserve.

The aftermath of the GFC also saw the rise of stress testing. A stress test assesses whether banks are sufficiently capitalized to withstand adverse scenarios. Effectively, the stress test represents a form of a forward-looking, bank-specific capital requirement. In early 2009, at the height of the crisis, the Supervisory Capital Assessment Program (SCAP)—subsequently replaced by the Comprehensive Capital Analysis and Review (CCAR)—represented the first stress testing effort. SCAP aimed to ensure that the 19 largest banks had sufficient capital coming out of the crisis to absorb losses under poor economic conditions. The Dodd-Frank Act formalized regular stress tests for the largest banks (DFAST) in 2013. Under CCAR, each bank must propose a capital distribution plan incorporated into the stress test, whereas DFAST uses a standardized capital distribution plan that holds dividends at their current level and sets net repurchases to zero. DFAST also requires banks to run (and disclose) stress tests using the same set of inputs (i.e., the Fed’s scenarios and the standard capital distribution plan) but with their own, internally developed model.

B Additional Results

B.1 Additional Results on Dynamics in Failing Banks

This subsection discusses additional results and robustness of the findings in [Section 4](#).

Additional results on declining solvency The patterns in [Figure 3b](#) suggest that failures are mainly associated with realized credit risk. How does the net interest margin (NIM) evolve in the run-up to failure? In [Appendix Figure B.1](#) we show that failing banks see both rising interest income (indicating higher risk taking) *and* rising interest expenses (in line with higher reliance on expensive forms of funding, as discussed below).

Further note that restricting our sample to the 1970s and 1980s and thus the period of the Volcker shock, 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.

It is important to highlight, however, that the resulting stable NIM does not suggest that the realization of interest rate risk cannot also be a source of trouble for failing banks. Making inference from NIM to interest rate exposure is problematic for various reasons (see, e.g., Begenau et al., 2015; Begenau and Stafford, 2022). While we believe our evidence is indicative that realized credit risk in the recent history of the U.S. has been a common cause of failure, we do not preclude that realized interest rate risk is not also a potentially important driver of bank failures.

Additional results on funding dynamics [Appendix Figure B.2](#) presents the dynamics of liabilities in logs, as opposed to as a share of assets. The figure shows that, in both the historical and modern sample, wholesale funding also rises at a similar pace in percentage terms as other forms of noncore funding. However, the rise is from a lower initial share of assets.

Additional results on asset boom and bust The boom-bust pattern in [Figure 6](#) is not simply driven by the fact that bank failures are more common at the end of a boom-bust cycle. First, the boom-bust pattern is similar for banks failing outside of major banking crises (see [Figure B.6](#)). Second, rapid asset growth predicts subsequent failure in the cross-section of banks (see [Figure B.7](#)). In contrast, at short horizons, banks with lowest growth are most likely to fail. The relation between asset growth and future failure is stronger in the 1959-2024 sample. For the historical sample, there is a strong relation between low growth and failure within one to three years, but a weaker relation between rapid growth and failure in five to six years (see [Appendix Figure B.8](#)).

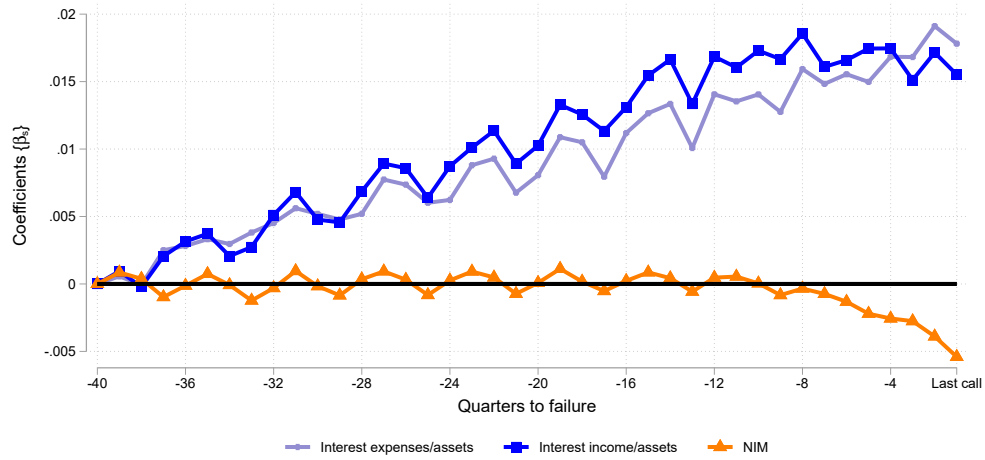
[Figure B.3](#) shows the estimates across finer subsamples. Asset growth prior to failure is especially large in the period leading up to the 2008 Global Financial Crisis, followed by the 1959-1981 and 1982-2006 periods. There are several potential explanations for why the boom-bust pattern has become stronger in the modern era. First, in the historical period, bank expansions were constrained by geographic restrictions, limiting the growth

of individual banks. Second, in recent decades, banks have greater access to more elastic non-core sources of funding, such as brokered deposits and funding in the Eurodollar market.¹ 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).

Figure B.4 shows that rapid asset growth is concentrated in illiquid loans. In contrast, liquid assets such as cash and securities rise more slowly than total assets. An implication of the rapid credit expansion in failing banks is that their asset holdings tilt increasingly towards illiquid loans that are associated with higher credit risk in the decade before failure. For the modern sample, Figure B.5 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.

¹Accounts 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).

Figure B.1: Interest Income, Expenses and NIM: 1959-2024



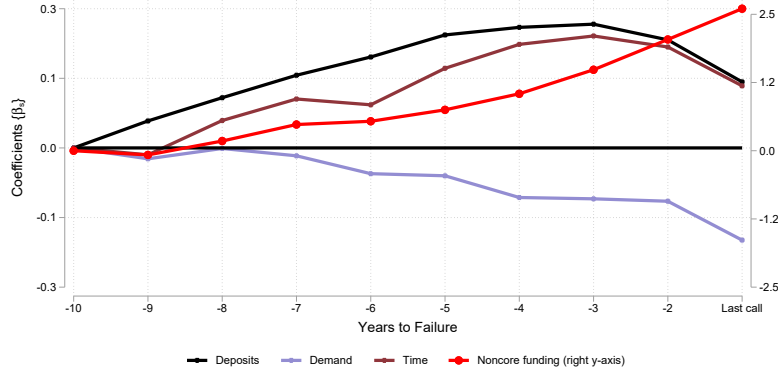
Notes: The figure shows the sequence of coefficients from a regression of the following form:

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

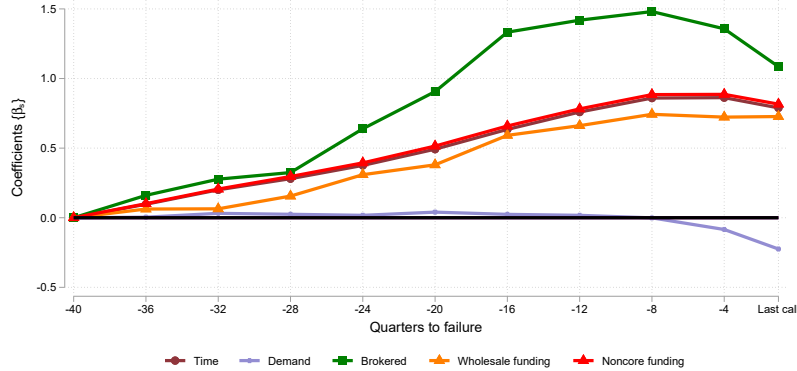
where y_{bt} is the ratio indicated in the figure legends, and α_b is a set of bank fixed effects. The sample is restricted to failing banks and to the ten years before they fail and banks that fail after 1959. The net interest margin (NIM) is defined as the difference between total interest income net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

Figure B.2: Funding of Failing Banks: Outcomes in Natural Logarithms

(a) 1863-1934: Deposits and Noncore Funding



(b) 1959-2024: Time, Demand, and Brokered Deposits, and Wholesale Funding



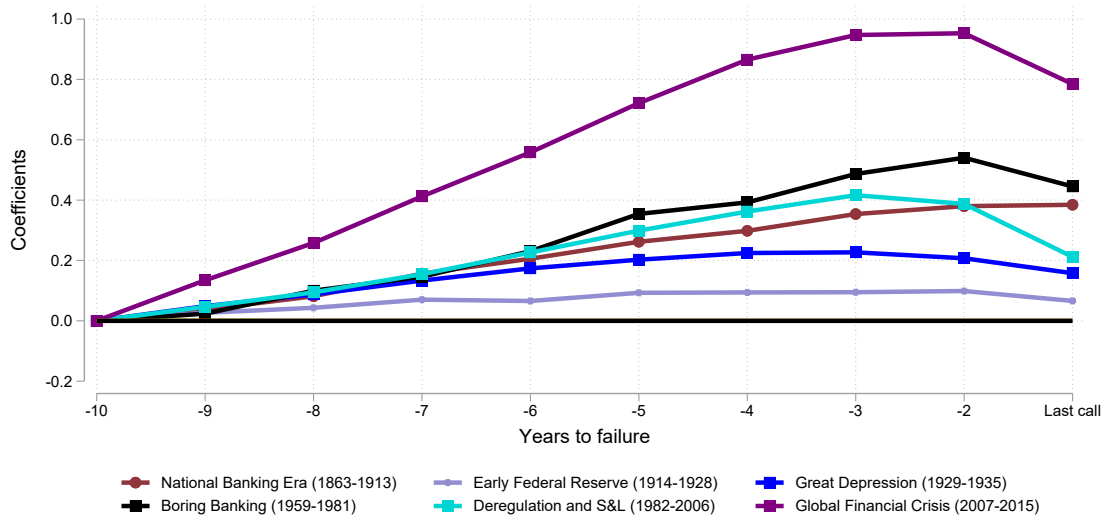
Notes: The figure shows the sequence of coefficients from a regression of the following form:

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

where y_{bt} is the natural logarithm of the line item indicated in the figure legends and α_b is a set of bank fixed effects. The sample is restricted to failing banks and to the ten years before they fail. In panel (a), the sample is restricted to data from 1863 through 1934 and in panel (b) to data from 1959 through 2024.

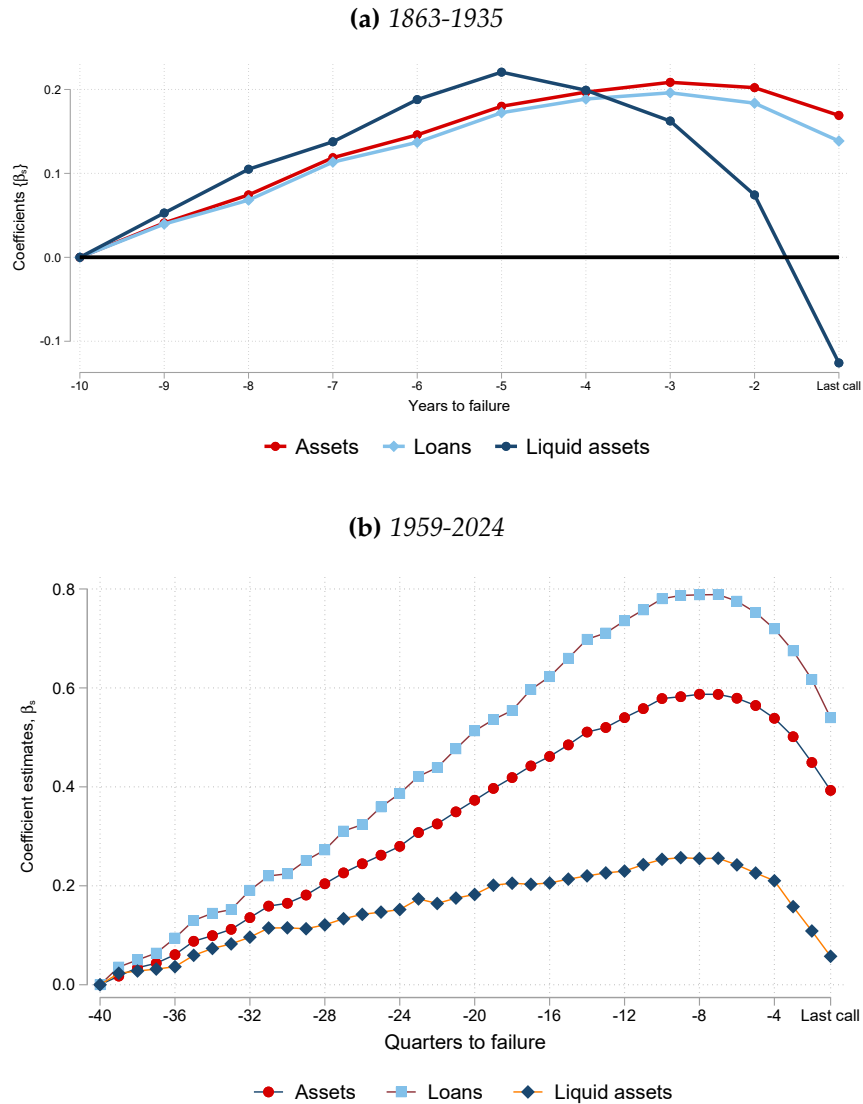
In panel (a) noncore funding is defined as the total assets net of total deposits (including unsecured interbank deposits), equity, and national bank notes. In panel (b), noncore funding is the sum of wholesale funding and time deposits, where wholesale funding is the amount reported in the call report 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. Note that for the historical sample, we do not include time deposits in noncore funding, as this item is only reported separately during 1915-1928.

Figure B.3: Assets in Failing Banks: 1863-2024, By Historical Subsamples



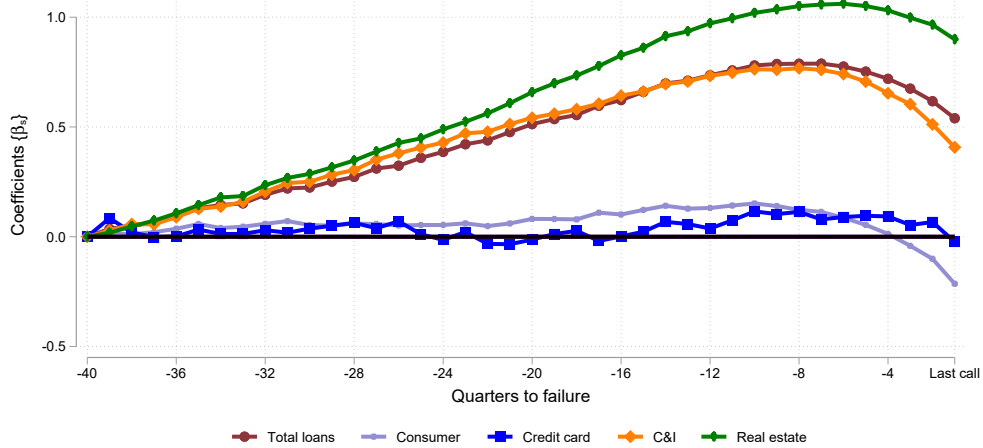
Notes: This figure reports the sequence of coefficients from estimating Equation (1) with log total assets (deflated by CPI) as the dependent variable for various subsamples. The regression includes a set of bank fixed effects. The sample is restricted to failing banks and to the ten years before they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

Figure B.4: Liquid and Illiquid Assets in Failing Banks



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, as well as FRS reserves after 1913. 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 B.5: Asset Growth in Failing Banks is Driven by Real Estate and C&I Lending

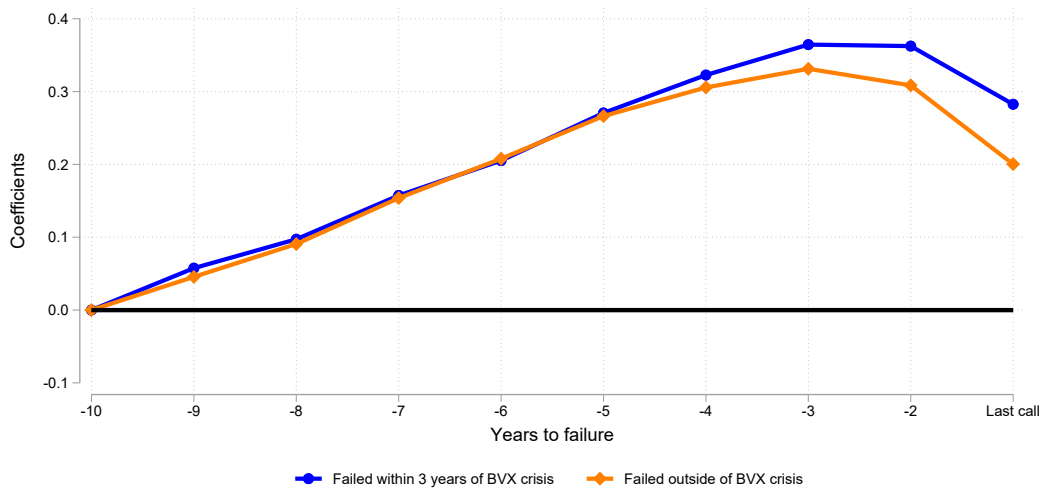


Notes: This figure presents the sequence of coefficients from a regression of the following form

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

where y_{bt} is a type of bank loan. The sample is restricted to failing banks and to the ten years before they fail. The estimates are based on the post-1959 sample. Data on loan types is not available for the pre-1935 sample.

Figure B.6: Asset Growth in Failing Banks for Failures Occurring during Financial Crises versus Normal Times

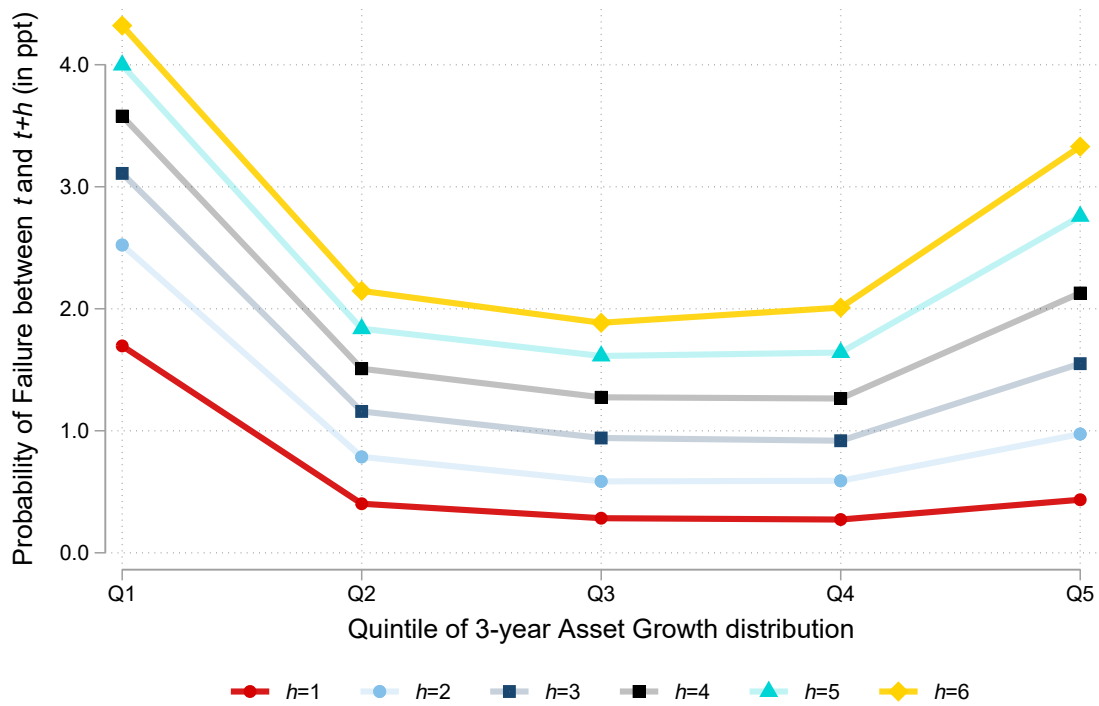


Notes: Both panels show the sequence of coefficients from a regression of the following form:

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

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

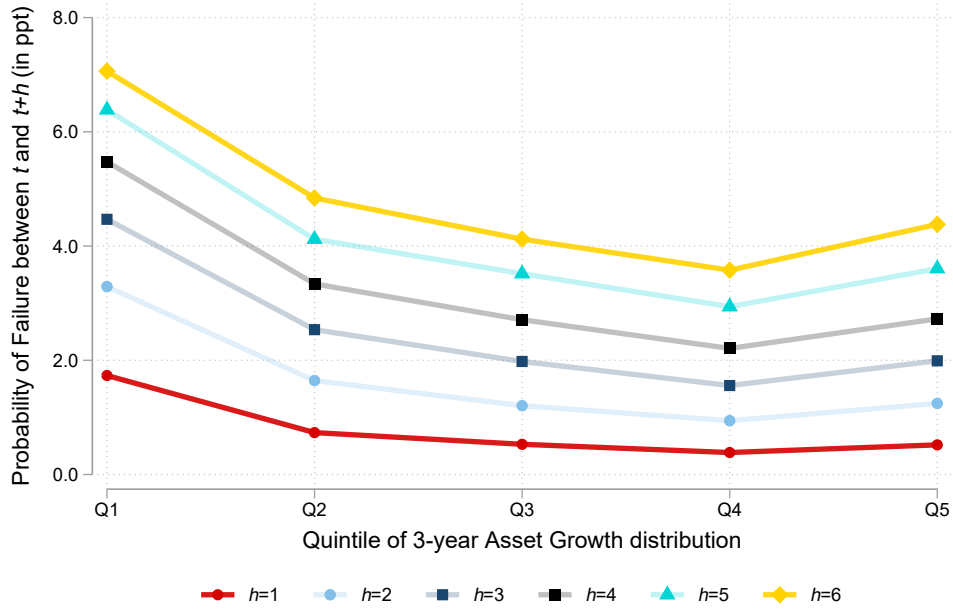
Figure B.7: Failure Probability in the Cross-Section of Asset Growth



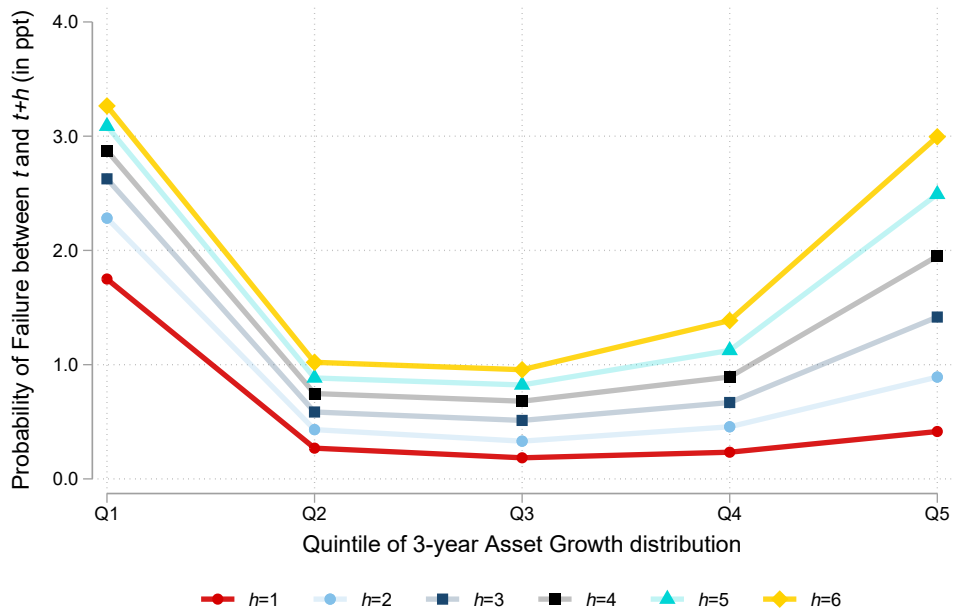
Notes: This figure plots the frequency of failure at the one to six year horizons across quintiles of the three-year asset growth distribution. Appendix [Figure B.8](#) shows this figure separately for the pre- and post-FDIC samples.

Figure B.8: Non-Monotonic Intertemporal Relation between Growth and Failure Probability

(a) Pre-1935

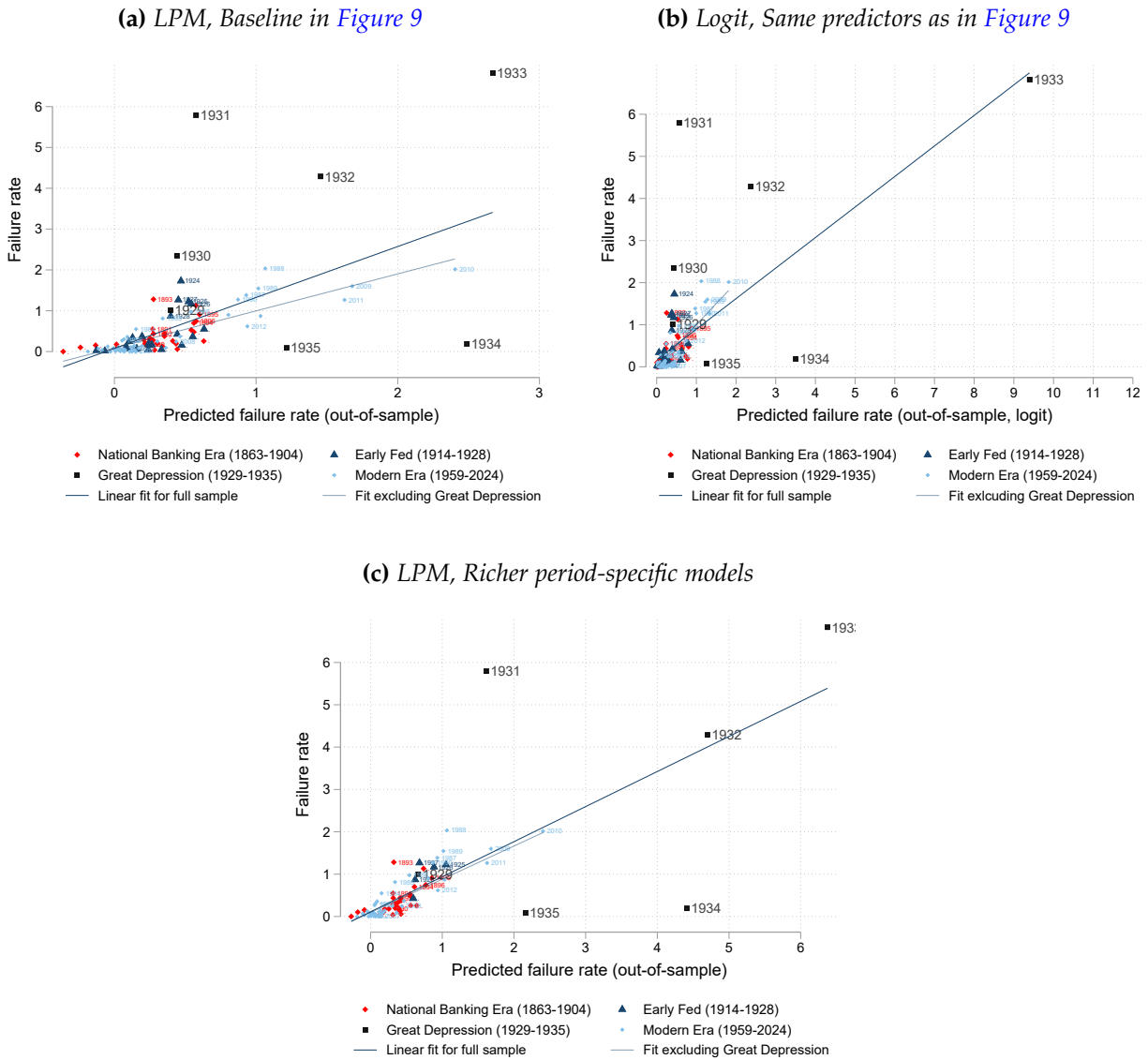


(b) Post-1935



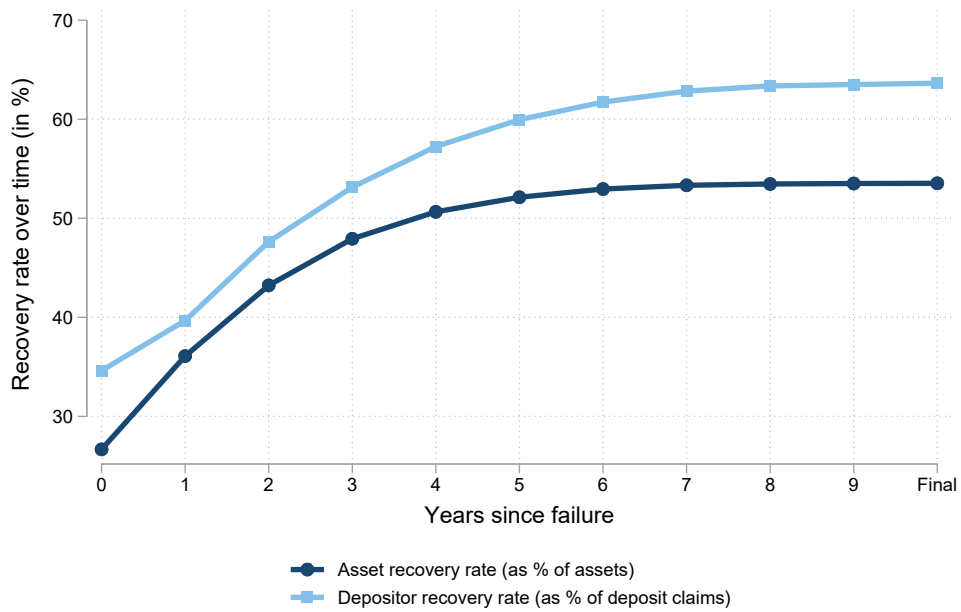
Notes: This figure plots the frequency of failure at the one to six year horizons across quintiles of the three-year asset growth distribution. Panel (a) presents the results for the 1863-1935 sample, and panel (b) presents the results for the 1959-2024 sample.

Figure B.9: Fundamentals Predict Aggregate Waves of Bank Failures: Robustness to Alternative Models



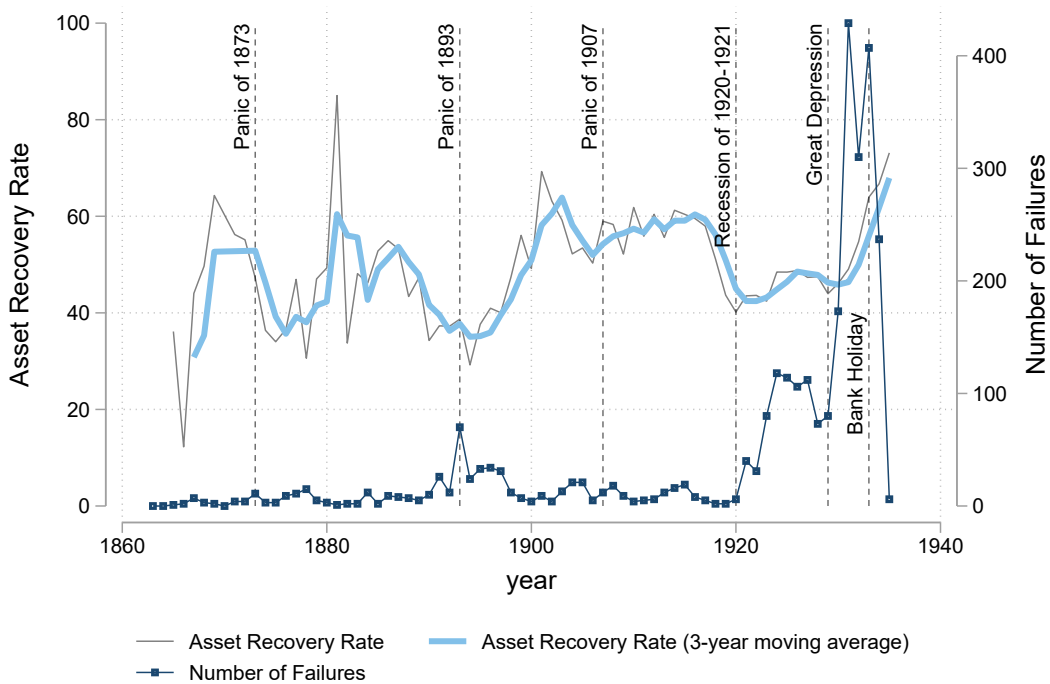
Notes: This figure plots the realized aggregate failure rate against the predicted aggregate failure rate, $\bar{p}_{t|t-1}$, based on various models of $\bar{p}_{t|t-1}$. Panels (a) and (c) use linear probability models, while panel (b) reports results from a logit model. Panels (a) and (b) use the baseline predictors from column (4) in Table 1. Panel (c) is based on the richer period-specific models in column (4) of Table B.5, Table B.8, Table B.9, and Table B.10. The predicted aggregate failure rate for year t is constructed using only information up to year $t - 1$, so the prediction is pseudo out-of-sample. Both measures start 10 years after the start of our data so that we have a sufficiently long training sample.

Figure B.10: Asset and Depositor Recovery Rate over Time Following Bank Failure: 1920-1939



Notes: The figure shows the average asset and depositor recovery rate as a function of the time since failure. The asset recovery rate is calculated as “collected from assets” divided by the sum of “assets at suspension” and the maximum reported “additional assets received after suspension.” The depositor recovery rate is the “dividend (in percent)” directly reported by the OCC. The sample covers bank failures from 1920 to 1939, as this sample allows us to observe the dividend payments to depositors in each year from the suspension to when the bank is finally closed. Data are collected from the OCC’s annual report to Congress, tables on “National banks in charge of receivers” (various years).

Figure B.11: Asset Recovery Rate over Time



Notes: This figure plots both the average and the three-year moving average of the recovery rate in receivership on the left y-axis and the number of total national bank failures on the right y-axis. The recovery rate is calculated as “collected from assets” divided by the sum of “assets at suspension” and the maximum reported “additional assets received after suspension.”

Table B.1: Summary Statistics: Bank-Level Data, 1863-1941

	N	Mean	Std. dev.	1st	10th	25th	75th	90th	99th
Failing bank	361,878	0.18	0.38	0.00	0.00	0.00	0.00	1.00	1.00
Surplus profit/equity	361,576	0.34	0.19	0.01	0.11	0.20	0.49	0.61	0.79
Noncore funding/assets	361,291	0.01	0.04	0.00	0.00	0.00	0.00	0.05	0.21
(Bills payable and rediscounts)/assets	178,266	0.01	0.04	0.00	0.00	0.00	0.00	0.04	0.18
Equity/assets	361,213	0.23	0.13	0.07	0.10	0.13	0.31	0.42	0.59
Loans/assets	361,144	0.52	0.26	0.13	0.30	0.42	0.64	0.71	0.81
Deposits/assets	355,621	0.63	0.20	0.12	0.33	0.50	0.79	0.86	0.92
Liquid assets/assets	355,794	0.18	0.11	0.04	0.07	0.10	0.23	0.32	0.53
OREO/loans	63,126	0.02	0.04	0.00	0.00	0.00	0.01	0.05	0.18
3-year asset growth (real)	346,631	-0.00	0.69	-1.94	-0.77	-0.31	0.30	0.77	1.94

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

Table B.2: Summary Statistics: Bank-Level Data, 1959-2024

	N	Mean	Std. dev.	1st	10th	25th	75th	90th	99th
Failing bank	2,528,198	0.06	0.24	0.00	0.00	0.00	0.00	0.00	1.00
Net income/assets	692,602	0.01	0.02	-0.03	0.00	0.01	0.01	0.02	0.03
Noncore funding/assets	2,441,622	0.36	0.17	0.00	0.10	0.25	0.49	0.56	0.70
Other borrowed money/assets	2,441,640	0.01	0.04	0.00	0.00	0.00	0.00	0.05	0.18
Deposits/assets	2,440,557	0.86	0.10	0.45	0.79	0.85	0.91	0.92	0.94
Time deposits/assets	2,403,753	0.35	0.16	0.00	0.11	0.24	0.48	0.55	0.67
Equity/assets	2,439,490	0.10	0.07	0.04	0.06	0.07	0.11	0.14	0.35
Loans/assets	1,926,615	0.57	0.16	0.08	0.36	0.47	0.68	0.77	0.89
Liquid assets/assets	2,441,047	0.38	0.16	0.06	0.17	0.26	0.49	0.60	0.80
Brokered deposits/assets	1,484,932	0.01	0.08	0.00	0.00	0.00	0.00	0.03	0.23
NPL/loans	1,397,374	0.02	0.03	0.00	0.00	0.00	0.02	0.04	0.13
LLP/loans	471,045	0.01	0.43	-0.00	0.00	0.00	0.01	0.01	0.07
NIM	1,941,223	0.01	0.01	-0.02	-0.00	0.00	0.02	0.03	0.05
3-year asset growth (real)	2,089,168	0.14	0.31	-0.38	-0.11	-0.01	0.23	0.42	1.32

Notes: This table reports summary statistics for the bank-level data based on 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 B.3: AUC Metric for Predicting Bank Failures with Fundamentals Using Richer Period-Specific Models

Prediction horizon h	1 year					3 years	5 years
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: National Banking Era (1863-1904)							
AUC (in-sample)	0.760	0.780	0.818	0.847	0.869	0.796	0.773
AUC (out-of-sample)	0.736	0.776	0.806	0.829	0.833	0.783	0.766
N	96044	95871	95871	94466	71591	94466	94466
No of Banks	5701	5698	5698	5542	5128	5542	5542
Mean of dep. var.	.37	.37	.37	.37	.24	1	1.6
Panel B: Early Federal Reserve (1914-1928)							
AUC (in-sample)	0.815	0.827	0.876	0.892	0.900	0.845	0.788
AUC (out-of-sample)	0.816	0.801	0.880	0.904	0.905	0.814	0.759
N	110443	110491	110443	109529	106636	109529	109529
No of Banks	9500	9500	9500	9433	9182	9433	9433
Mean of dep. var.	.61	.61	.61	.61	.34	2.4	5.3
Panel C: Great Depression (1929-1934)							
AUC (in-sample)	0.748	0.773	0.822	0.833	0.823	0.806	0.808
AUC (out-of-sample)	0.638	0.730	0.731	0.727	0.674	0.705	0.736
N	35102	35104	35102	34996	34720	34996	34996
No of Banks	7461	7461	7461	7451	7303	7451	7451
Mean of dep. var.	3.5	3.5	3.5	3.5	1.7	9.8	12
Specification details							
Insolvency	✓		✓	✓	✓	✓	✓
Noncore funding		✓	✓	✓	✓	✓	✓
Insolvency × Noncore funding			✓	✓	✓	✓	✓
Growth & Aggregate conditions				✓	✓	✓	✓
Deposit outflow before failure					>7.5%		
Age controls	✓	✓	✓	✓	✓	✓	✓

Notes: This table reports the area under the receiver operating characteristic curve (AUC) across different specifications, samples, and horizons using in-sample and pseudo-out-of-sample classification. The corresponding regression coefficients underlying the models for Panel A can be found in [Table B.8](#), for Panel B in [Table B.9](#), and for Panel C in [Table B.10](#). Pseudo-out-of-sample AUCs are obtained by estimating the regression model with an initial training sample from 1863-1873 (Panel A), 1914-1919 (Panel B), and 1880-1904 (Panel C). In column (5) of Panel A, we restrict the sample to data from 1880 onward, and out-of-sample predictions are based on an initial training sample from 1880-1890.

Table B.4: Regression Models Predicting Bank Failures: 1863-1934

Horizon h	Fail in next year					3 years	5 years
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Withdrawals before failure					>7.5%		
Solvency:							
- Surplus/Equity	-3.38*** (1.16)		-1.57*** (0.58)	-1.19** (0.49)	-0.54** (0.27)	-2.87** (1.12)	-2.78** (1.31)
Funding:							
- Noncore Funding/Assets		34.81*** (10.05)	64.47*** (16.18)	64.06*** (15.13)	32.93*** (6.71)	120.80*** (18.20)	142.57*** (17.06)
Solvency \times Funding:							
- Surplus/Equity \times Noncore Fund./Assets			-91.66*** (19.35)	-94.14*** (19.02)	-47.13*** (8.58)	-139.37*** (17.54)	-142.95*** (22.17)
Bank Growth:							
- Q1 of Growth from t-3 to t				0.87*** (0.30)	0.56*** (0.21)	1.83*** (0.66)	2.12*** (0.79)
- Q2 of Growth from t-3 to t				0.12* (0.07)	0.08* (0.05)	0.40** (0.19)	0.41* (0.22)
- Q4 of Growth from t-3 to t				-0.10 (0.08)	-0.06 (0.05)	-0.30 (0.19)	-0.43* (0.23)
- Q5 of Growth from t-3 to t				-0.08 (0.08)	-0.06 (0.04)	-0.04 (0.16)	0.09 (0.26)
Aggregate Conditions:							
- GDP Growth from t-3 to t				-4.07 (2.52)	-0.56 (0.93)	-6.68 (4.52)	-3.93 (5.02)
- CPI Inf. from t-3 to t				-0.91 (0.59)	-0.65* (0.35)	-3.45 (2.16)	-4.23 (3.64)
N	294574	294253	294247	290088	262636	290088	290088
No of Banks	12536	12535	12535	12428	11851	12428	12428
Mean of dep. var.	.79	.79	.79	.8	.45	2.5	4.1

Notes: This table presents OLS estimates of Equation (2) with failure between t and $t + h$ as the dependent variables for the 1863-1934 sample. In addition to the reported predictor variables, we also include the log of a bank's age. Driscoll and Kraay (1998) standard errors in parentheses with bandwidth $h = 2$; *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table B.5: Regression Models Predicting Bank Failures: 1959-2024

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	-72.64*** (25.45)		16.54*** (3.92)	17.70*** (4.13)	1.56** (0.68)	20.79*** (3.88)	20.17*** (3.69)
Noncore funding:							
- Noncore Funding/Assets		2.41*** (0.82)	5.20*** (0.77)	5.46*** (0.82)	0.52*** (0.12)	11.07*** (1.90)	13.66*** (2.35)
Solvency \times Noncore funding:							
- NI/Assets \times Noncore Fund./Assets			-426.31*** (67.48)	-428.38*** (67.63)	-42.93*** (11.23)	-660.42*** (94.50)	-684.30*** (95.61)
Bank Growth:							
- Q1 of Growth from t-3 to t				0.13** (0.06)	-0.00 (0.02)	0.40*** (0.12)	0.56*** (0.15)
- Q2 of Growth from t-3 to t				-0.06* (0.03)	0.00 (0.01)	-0.11** (0.05)	-0.11** (0.05)
- Q4 of Growth from t-3 to t				0.04 (0.03)	0.01 (0.01)	0.10* (0.05)	0.22** (0.09)
- Q5 of Growth from t-3 to t				-0.07 (0.05)	-0.00 (0.01)	0.24 (0.16)	0.80** (0.34)
Aggregate Conditions:							
- GDP Growth from t-3 to t				0.67 (0.93)	0.25 (0.36)	3.78 (3.92)	4.57 (6.03)
- CPI Inf. from t-3 to t				0.06 (0.24)	0.40** (0.19)	-0.42 (0.91)	1.05 (1.85)
N	633407	633404	633404	590645	215320	590645	590645
No of Banks	23107	23106	23106	22348	13900	22348	22348
Mean of dep. var.	.32	.32	.32	.34	.032	.97	1.5

Notes: This table presents OLS estimates of Equation (2) with failure between t and $t + h$ as the dependent variables for the 1959-2024 sample. In addition to the reported predictor variables, we also include the log of a bank's age. The sample in column (5) is restricted to the years from 1993-2024 due to the unavailability to deposits in failure before 1993. Driscoll and Kraay (1998) standard errors in parentheses with bandwidth $h = 2$; *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table B.6: AUC Metric for Predicting Bank Failures with Fundamentals Using Logit Model

Prediction horizon h	1 year				3 years	5 years	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Historical Sample (1863-1934)							
AUC (in-sample)	0.685	0.798	0.803	0.863	0.857	0.802	0.736
AUC (out-of-sample)	0.768	0.838	0.836	0.854	0.843	0.813	0.775
N	294574	294253	294247	290088	262636	290088	290088
No of Banks	12536	12535	12535	12428	11851	12428	12428
Mean of dep. var.	.79	.79	.79	.8	.45	2.5	4.1
Panel D: Modern Sample (1959-2024)							
AUC (in-sample)	0.946	0.850	0.949	0.949	0.900	0.902	0.856
AUC (out-of-sample)	0.916	0.830	0.938	0.939	0.893	0.879	0.825
N	633407	633404	633404	590645	215320	590645	590645
No of Banks	23107	23106	23106	22348	13900	22348	22348
Mean of dep. var.	.32	.32	.32	.34	.032	.97	1.5
Specification details							
Insolvency	✓		✓	✓	✓	✓	✓
Noncore funding		✓	✓	✓	✓	✓	✓
Insolvency × Noncore funding			✓	✓	✓	✓	✓
Growth & Aggregate conditions				✓	✓	✓	✓
Deposit outflow before failure					>7.5%		
Age controls	✓	✓	✓	✓	✓	✓	✓

Notes: This table reports the area under the receiver operating characteristic curve (AUC) across different specifications, samples, and horizons using in-sample and pseudo-out-of-sample classification. The predictions are based on logit models with the same predictive variables in each column as in [Table 1](#). Pseudo-out-of-sample AUCs are obtained by estimating the regression model on an initial training sample from 1863-1873 (Panel A) and 1959-1969 (Panel B) and iteratively expanding the sample for subsequent years. We drop banks without information on deposit outflow before failure in column (5), restricting the sample period to 1880-1934 in Panel (A), as data on deposits at failure are not available before 1880. Similarly, column (5) in Panel B is restricted to the years from 1993-2024, deposits in failure are not available before 1993.

Table B.7: AUC Metric for Predicting Bank Failures with Fundamentals by Size

Predictions horizon h	1 year				
	1st	2nd	3rd	4th	5th
Size Quintile	(1)	(2)	(3)	(4)	(5)
Panel A: Historical Sample (1863-1934)					
AUC (in-sample)	0.846	0.864	0.864	0.866	0.869
AUC (out-of-sample)	0.830	0.855	0.846	0.856	0.831
N	56575	58105	58386	58540	58482
No of Banks	6548	6831	6106	4784	3127
Mean of dep. var.	1.3	.93	.69	.57	.49
Panel B: Modern Era (1959-2024)					
AUC (in-sample)	0.954	0.951	0.951	0.943	0.949
AUC (out-of-sample)	0.952	0.944	0.941	0.940	0.938
N	122948	122309	121169	117936	106283
No of Banks	7251	10155	10912	9614	6695
Mean of dep. var.	.44	.32	.29	.27	.37
Specification details					
Insolvency	✓	✓	✓	✓	✓
Noncore funding	✓	✓	✓	✓	✓
Insolvency \times Noncore funding	✓	✓	✓	✓	✓
Age controls	✓	✓	✓	✓	✓

Notes: This table reports the area under the receiver operating characteristic curve (AUC) for column (4) of [Table B.4](#) (Panel A) and [Table B.5](#) (Panel B) when splitting the sample into five different size categories. Size categories correspond to quintiles of the assets distribution, calculated within a given year. Pseudo-out-of-sample AUCs are obtained by estimating the regression model with an initial training sample of 10 years and iteratively expanding the sample for subsequent years.

Table B.8: Predicting Bank Failures: Richer Period-Specific Models for 1863-1904

Horizon h	Fail in next year					3 years	5 years
						>7.5%	
Withdrawals before failure	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Solvency:							
- Surplus/Equity	-1.26*** (0.26)	-0.60*** (0.14)	-0.55*** (0.13)	-0.15* (0.08)	-1.88*** (0.33)	-2.49*** (0.40)	
- Dividend Payout Restricted	1.71*** (0.56)	0.70*** (0.24)	0.67*** (0.23)	0.65*** (0.19)	1.44*** (0.50)	1.69*** (0.59)	
- Equity/Assets	-1.03*** (0.29)	-0.93*** (0.23)	-1.64*** (0.26)	-0.92*** (0.25)	-4.40*** (0.66)	-6.73*** (0.91)	
- Loans/Assets	1.32*** (0.34)	0.53** (0.26)	0.38 (0.24)	-0.14 (0.19)	1.66*** (0.41)	3.07*** (0.54)	
Noncore funding:							
- (Bills Payable + Rediscounts)/Assets		17.38*** (3.79)	27.59*** (5.11)	27.48*** (5.36)	17.39*** (3.74)	53.57*** (12.40)	71.43*** (13.28)
Solvency \times Noncore funding:							
- Surplus/Equity \times (Bills Pay. + Redis.)/Assets			-57.92*** (12.34)	-56.57*** (13.31)	-35.02*** (9.70)	-102.55*** (26.93)	-130.79*** (26.14)
- Div. Restricted \times (Bills Pay. + Redis.)/Assets			52.00*** (17.40)	52.19*** (17.05)	36.98** (15.94)	53.83*** (17.55)	43.61** (18.73)
Bank Growth:							
- Q1 of Growth from t-3 to t				0.46*** (0.12)	0.31*** (0.09)	0.90*** (0.27)	0.98*** (0.28)
- Q2 of Growth from t-3 to t				0.14*** (0.05)	0.12** (0.06)	0.19** (0.09)	0.10 (0.10)
- Q4 of Growth from t-3 to t				0.03 (0.08)	0.02 (0.06)	-0.02 (0.09)	-0.03 (0.09)
- Q5 of Growth from t-3 to t				-0.07 (0.05)	-0.11** (0.05)	0.04 (0.16)	0.05 (0.24)
Aggregate Conditions:							
- GDP Growth from t-3 to t				-1.69*** (0.47)	-0.91** (0.41)	-3.94*** (1.48)	-4.80** (1.89)
- CPI Inf. from t-3 to t				-0.71 (0.62)	-0.87 (0.70)	-1.32 (1.68)	-0.93 (2.36)
N	96044	95871	95871	94466	71591	94466	94466
No of Banks	5701	5698	5698	5542	5128	5542	5542
Mean of dep. var.	.37	.37	.37	.37	.24	1	1.6

Notes: This table presents OLS estimates of (2) with failure between t and $t + h$ as the dependent variables for the 1863-1904 sample. In addition to the reported predictor variables, we also include the log of a bank's age. Driscoll and Kraay (1998) standard errors in parentheses with bandwidth $h = 2$; *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table B.9: Predicting Bank Failures: Richer Period-Specific Models for 1914-1928

Horizon h	Fail in next year					3 years	5 years
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Withdrawals before failure					>7.5%		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Solvency:							
- Surplus/Equity	-4.01*** (1.24)		-1.63*** (0.53)	-1.18*** (0.35)	-0.59*** (0.19)	-4.80*** (1.40)	-8.67*** (2.40)
- Loans/Assets	0.56*** (0.19)		0.22* (0.12)	0.22* (0.13)	0.12* (0.07)	1.03* (0.55)	2.32* (1.23)
- Equity/Assets	-2.06** (0.88)		-1.99** (0.97)	-3.11** (1.28)	-1.93** (0.80)	-15.23*** (4.28)	-33.95*** (8.61)
Noncore funding:							
- Noncore funding/Assets		25.31*** (6.50)	52.45*** (12.57)	52.32*** (11.83)	31.88*** (8.86)	114.89*** (13.46)	138.08*** (13.72)
Solvency \times Noncore funding:							
- Surplus/Equity \times Noncore funding/Assets			-82.99*** (20.15)	-83.86*** (19.28)	-51.31*** (14.22)	-162.95*** (21.30)	-176.14*** (20.15)
- Loans/Assets \times Noncore funding/Assets			0.67 (0.87)	0.64 (0.81)	-0.11 (0.34)	0.15 (2.73)	-1.79 (3.97)
Bank Growth:							
- Q1 of Growth from t-3 to t				1.02*** (0.36)	0.61*** (0.21)	2.91*** (0.98)	3.91*** (1.21)
- Q2 of Growth from t-3 to t				0.07** (0.03)	0.06** (0.03)	0.60*** (0.18)	0.91*** (0.27)
- Q4 of Growth from t-3 to t				-0.07 (0.06)	-0.03 (0.04)	-0.35** (0.16)	-0.97*** (0.33)
- Q5 of Growth from t-3 to t				-0.13 (0.11)	-0.08 (0.07)	-0.67** (0.28)	-1.30** (0.53)
Aggregate Conditions:							
- GDP Growth from t-3 to t				2.04* (1.07)	1.57** (0.76)	3.44 (2.22)	3.16 (7.14)
- CPI Inf. from t-3 to t				-0.64** (0.31)	-0.38* (0.21)	-3.60** (1.67)	-7.53* (4.09)
N	110443	110491	110443	109529	106636	109529	109529
No of Banks	9500	9500	9500	9433	9182	9433	9433
Mean of dep. var.	.61	.61	.61	.61	.34	2.4	5.3

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. Driscoll and Kraay (1998) standard errors in parentheses with bandwidth $h = 2$; *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table B.10: Regression Models Predicting Bank Failures: Richer Period-Specific Models for 1929-1934

Horizon h	Fail in next year					3 years	5 years
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Withdrawals before failure					>7.5%		
Solvency:							
- Equity/Assets	-9.53*** (2.85)		-10.82*** (2.63)	-15.26*** (4.42)	-7.69** (3.60)	-43.56*** (12.93)	-54.47*** (18.28)
- Surplus/Equity	-10.99*** (3.90)		-4.08** (1.99)	-2.38** (0.94)	-1.76 (1.10)	-10.21** (4.68)	-9.82* (5.52)
- Dividend Payout Restricted	3.34*** (0.46)		1.79*** (0.34)	1.51*** (0.31)	0.27** (0.13)	1.60** (0.72)	1.04 (1.20)
- Loans/Assets	12.01*** (1.85)		4.51*** (0.93)	4.10*** (1.35)	2.31** (1.12)	13.31*** (3.64)	17.73*** (4.25)
Noncore funding:							
- (Bills Payable + Rediscounts)/Assets		99.29*** (8.51)	169.76*** (13.08)	166.42*** (13.71)	57.92*** (19.59)	243.52*** (19.78)	245.73*** (19.71)
Solvency \times Noncore funding:							
- Surplus/Equity \times (Bills Pay. + Redis.)/Assets			-224.58*** (16.47)	-218.83*** (18.20)	-60.57*** (20.40)	-217.17*** (25.53)	-191.81*** (18.72)
- Div. Payout Restr. \times (Bills Pay. + Redis.)/Assets			9.55 (14.71)	10.15 (13.53)	12.57 (8.60)	-7.65 (18.11)	-14.82 (14.63)
Bank Growth:							
- Q1 of Growth from t-3 to t				2.80*** (1.07)	1.70** (0.79)	4.16** (1.76)	4.35** (1.93)
- Q2 of Growth from t-3 to t				0.52* (0.27)	0.26 (0.22)	1.57*** (0.60)	1.72*** (0.66)
- Q4 of Growth from t-3 to t				-0.86*** (0.28)	-0.46** (0.20)	-2.16*** (0.81)	-2.35** (0.98)
- Q5 of Growth from t-3 to t				-0.81** (0.35)	-0.36 (0.24)	-1.92** (0.83)	-2.49** (1.25)
Aggregate Conditions:							
- GDP Growth from t-3 to t				-0.98 (45.05)	0.13 (30.56)	106.34 (95.01)	143.51 (105.54)
- CPI Inf. from t-3 to t				-0.22 (68.87)	9.62 (46.03)	-132.53 (145.79)	-153.03 (170.23)
N	35102	35104	35102	34996	34720	34996	34996
No of Banks	7461	7461	7461	7451	7303	7451	7451
Mean of dep. var.	3.5	3.5	3.5	3.5	1.7	9.8	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. Driscoll and Kraay (1998) standard errors in parentheses with bandwidth $h = 2$; *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table B.11: Predicting Bank Failures: True Positives, False Positives, True Negatives, and False Negatives from Linear Probability Model

c	TPR	FPR	TNR (= 1 - FPR)	FNR (= 1 - TPR)
Panel A: Historical Sample (1863-1934)				
0.8%	0.856	0.311	0.689	0.144
1%	0.818	0.252	0.748	0.182
1.5%	0.726	0.147	0.853	0.274
2%	0.659	0.096	0.904	0.341
2.5%	0.597	0.073	0.927	0.403
3%	0.545	0.059	0.941	0.455
4%	0.468	0.040	0.960	0.532
5%	0.390	0.028	0.972	0.610
10%	0.151	0.006	0.994	0.849
Panel B: Modern Sample (1959-2024)				
0.3%	0.958	0.367	0.633	0.042
0.5%	0.952	0.279	0.721	0.048
1%	0.933	0.144	0.856	0.067
1.5%	0.908	0.083	0.917	0.092
2%	0.889	0.055	0.945	0.111
2.5%	0.866	0.040	0.960	0.134
3%	0.837	0.031	0.969	0.163
4%	0.786	0.021	0.979	0.214
5%	0.738	0.015	0.985	0.262
10%	0.512	0.004	0.996	0.488

Notes: This table reports the true positive rate (TPR), false positive rate (FPR), true negative rate (TNR), and false negative rate (FNR) based on different cutoffs (c) for classifying failures. Specifically, we classify a bank as predicted to fail if the $\Pr[Failure_{b,t+1}] > c$. Predicted values are based on column (4) from [Table B.4](#) in Panel A and (4) of [Table B.5](#) in Panel B using a linear probability model.

Table B.12: Predicting Bank Failures: True Positives, False Positives, True Negatives, and False Negatives from Logit Model

c	TPR	FPR	TNR (= 1 - FPR)	FNR (= 1 - TPR)
Panel A: Historical Sample (1863-1934)				
0.8%	0.774	0.203	0.797	0.226
1%	0.721	0.154	0.846	0.279
1.5%	0.623	0.088	0.912	0.377
2%	0.542	0.058	0.942	0.458
2.5%	0.487	0.042	0.958	0.513
3%	0.437	0.033	0.967	0.563
4%	0.367	0.022	0.978	0.633
5%	0.317	0.017	0.983	0.683
10%	0.183	0.006	0.994	0.817
Panel B: Modern Sample (1959-2024)				
0.3%	0.899	0.128	0.872	0.101
0.5%	0.850	0.063	0.937	0.150
1%	0.753	0.024	0.976	0.247
1.5%	0.700	0.015	0.985	0.300
2%	0.656	0.011	0.989	0.344
2.5%	0.617	0.009	0.991	0.383
3%	0.592	0.008	0.992	0.408
4%	0.543	0.006	0.994	0.457
5%	0.508	0.005	0.995	0.492
10%	0.395	0.003	0.997	0.605

Notes: This table reports the true positive rate (TPR), false positive rate (FPR), true negative rate (TNR), and false negative rate (FNR) based on different cutoffs (c) for classifying failures. Specifically, we classify a bank as predicted to fail if the $\Pr[Failures_{b,t+1}] > c$. Predicted values are based on specification (4) from [Table B.4](#) in Panel A and (4) of [Table B.5](#) in Panel B using a logit model.

Table B.13: Precision-Recall Curve for Predicting Bank Failures

Prediction horizon h	1 year				3 years	5 years	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Historical Sample (1863-1934), Baseline Models in Table 1							
PR-AUC (in-sample)	0.026	0.059	0.076	0.087	0.042	0.145	0.143
PR-AUC (out-of-sample)	0.033	0.082	0.109	0.110	0.045	0.170	0.184
Mean of dep. var.	0.008	0.008	0.008	0.008	0.004	0.025	0.025
Ratio (in-sample)	3.250	7.382	9.544	10.909	9.441	5.764	5.673
Ratio (out-of-sample)	4.054	10.129	13.380	13.485	9.364	6.605	7.148
Precision at 10% recall (in-smp.)	0.059	0.121	0.157	0.177	0.073	0.236	0.232
Precision at 10% recall (o.o.s.)	0.054	0.147	0.181	0.190	0.071	0.296	0.308
Panel B: Modern Sample (1959-2024), Baseline Models in Table 1							
PR-AUC (in-sample)	0.212	0.034	0.297	0.298	0.050	0.282	0.283
PR-AUC (out-of-sample)	0.218	0.022	0.288	0.287	0.040	0.273	0.279
Mean of dep. var.	0.0032	0.0032	0.0032	0.0034	0.0003	0.0097	0.0097
Ratio (in-sample)	66.128	10.677	92.814	87.826	155.200	29.107	29.255
Ratio (out-of-sample)	56.932	5.742	75.395	75.115	102.984	25.029	25.637
Precision at 10% recall (in-smp.)	0.330	0.050	0.453	0.453	0.071	0.509	0.508
Precision at 10% recall (o.o.s.)	0.372	0.027	0.466	0.465	0.068	0.507	0.516
Specification details							
Insolvency	✓		✓	✓	✓	✓	✓
Noncore funding		✓	✓	✓	✓	✓	✓
Insolvency × Noncore funding			✓	✓	✓	✓	✓
Growth & Aggregate conditions				✓	✓	✓	✓
Deposit outflow before failure					>7.5%		
Age controls	✓	✓	✓	✓	✓	✓	✓

Notes: This table reports the area under the precision-recall curve (PR-AUC), the mean failure rate, and precision at 10% recall across different specifications, samples, and horizons using in-sample and pseudo-out-of-sample classification. Ratio refers to the ratio of the PR-AUC and the mean of the dependent variable, which would be the precision of a naive model that classified all observations as failures. The models used are equivalent to the models in the corresponding column of Table 1. The corresponding regression coefficients underlying the models are reported in Table B.4 (for Panel A) and Table B.5 (for Panel B). The PR-AUC is based on predictions from linear probability models. We drop banks without information on deposit outflows before failure in column (5). This restricts the sample period to 1880-1934 in Panel (A) and 1993-2024 in Panel (B), as data on deposits at failure are not available before 1880 and 1993 respectively.

Table B.14: *Out-of-sample Predicted Probability of Failure Before Failure, 1875-1934*

Panel A1: OOS Predicted Probability of Failure ($h = 1$)									
Model	Avg.	Med.	Share by Predicted Probability of Failure						
			[0,1%)	[1%,5%)	[5%,10%)	[10%,20%)	[20%,30%)	[30%,40%)	≥ 40
Baseline	0.07	0.02	0.40	0.32	0.10	0.08	0.04	0.03	0.04
Richer model	0.18	0.06	0.23	0.25	0.11	0.11	0.06	0.05	0.18
Panel A2: OOS Predicted Probability of Failure ($h = 3$)									
Baseline	0.14	0.05	0.13	0.38	0.15	0.12	0.07	0.05	0.12
Richer Model	0.32	0.20	0.06	0.20	0.10	0.13	0.08	0.07	0.34
Panel B1: Required Excess Return (risk neutral)									
	Avg.	Med.	Share by Implied Required Excess Return						
			<0.5%	[0.5%,1%)	[1%,2.5%)	[2.5%,5%)	[5%,10%)	[10%,15%)	≥ 15
Baseline	0.04	0.01	0.46	0.13	0.16	0.09	0.07	0.03	0.06
Richer model	0.10	0.02	0.28	0.10	0.16	0.11	0.10	0.06	0.20
Panel B2: Required Excess Return (log-utility)									
Baseline	0.05	0.01	0.41	0.13	0.17	0.10	0.07	0.04	0.08
Richer model	0.10	0.02	0.26	0.11	0.16	0.11	0.11	0.06	0.20
Panel B3: Required Excess Return (CRRA, $\gamma = 5$)									
Baseline	0.13	0.05	0.28	0.04	0.08	0.10	0.12	0.09	0.30
Richer model	0.17	0.10	0.16	0.03	0.08	0.10	0.12	0.13	0.39

Notes: Panels A1 and A2 report the distribution of the bank-level out-of-sample predicted probabilities of failure over the one-year and three-year horizon for failing banks as of the last call report before failure for all failures from 1873 through 1934. The predicted values in the baseline model reported in the first row result from estimating the model reported in Column (4) of Table B.4 using logit. The predicted probabilities of the model reported in the second row are from estimating the richer models that use a different set of ratios and different training sample across the National Banking Era, Early Federal Reserve, and Great Depression and are reported in column (4) of Table B.8, Table B.9, and Table B.10, respectively using logit.

Panels B1 and B2 shows the distribution of the required excess return on deposits (trimmed at 100%). We calculate the required excess return on deposits, $s_{b,t}$, as the solution to the following equation:

$$(1 - \hat{p}_{b,t+1|t})u(1 + r_t + s_{b,t}) + \hat{p}_{b,t+1|t}u(1 - \ell_{t+1|t}) = u(1),$$

where $\ell_{t+1|t}$ is the loss rate on failures up to time t and r_t is the rate on treasury bills in year t . Note that this assumes that the certainty equivalent earns a return of zero. We assume $u(x) = x$ in Panel B1, $u(c) = \ln(c)$ in Panel B2, and $u(c) = \frac{c^{1-\gamma}}{1-\gamma}$ with $\gamma = 5$ in Panel B3.

Table B.15: Predictability of Failures By Era and During Major Banking Crises

Panel A: 1863-1935						
	1890	1893	1890-1896	1930-1933	1929-1931	1932-1933
AUC	0.851	0.819	0.796	0.758	0.776	0.861
Panel B: 1959-2024						
	1959-1981	1982-1994	1994-2006	2007-2024	1984-1990	2007-2013
AUC	0.848	0.951	0.862	0.966	0.956	0.967

Notes: This table reports the area under the receiver operating characteristic curve (AUC) by sample period. In Panel A, we calculate the AUC based on the predictions obtained from the model in column (4) of [Table B.4](#). In Panel B, we calculate the AUC based on the predictions obtained from the model in column (4) of [Table B.5](#).

Table B.16: Fundamentals Predict Aggregate Rate of Bank Failures: Robustness Using Alternative Models

Dependent variable	Aggregate Failure Rate			
Panel A: LPM, Same Predictors as in Columns (1)-(4) of Table 1				
	(1)	(2)	(3)	(4)
Predicted failure rate, $\bar{p}_{t t-1}$	1.86*** (0.34)	2.64*** (0.77)	1.57*** (0.59)	1.25*** (0.24)
Constant	0.14 (0.09)	-0.31 (0.20)	0.01 (0.09)	0.08 (0.05)
N	117	117	117	117
R ²	0.21	0.47	0.40	0.40
Table 1 model	Col. 1	Col. 2	Col. 3	Col. 4
Sample	Full	Full	Full	Full
Panel B: Logit, Same Predictors as in Columns (4) of Table 1				
	(1)	(2)	(3)	(4)
Predicted failure rate, $\bar{p}_{t t-1}$	0.73*** (0.06)	0.68*** (0.04)	1.24*** (0.11)	1.00*** (0.15)
Constant	0.17 (0.11)	0.31 (0.19)	-0.14* (0.08)	0.00 (0.08)
N	116	60	55	110
R ²	0.50	0.47	0.82	0.50
Sample	Full	1874-1934	1970-2024	Exclude 1929-1934
Panel C: LPM, Richer Period-Specific Models				
	(1)	(2)	(3)	(4)
Predicted failure rate, $\bar{p}_{t t-1}$	0.83*** (0.08)	0.83*** (0.10)	0.97*** (0.15)	0.78*** (0.15)
Constant	0.11** (0.05)	0.16 (0.11)	0.06 (0.04)	0.10** (0.04)
N	97	41	55	92
R ²	0.59	0.56	0.81	0.58
Sample	Full	1874-1934	1970-2024	Exclude 1929-1934

Notes: This table presents time series regressions of the annual aggregate failure rate in year t on the average predicted failure rate $\bar{p}_{t|t-1}$. The average predicted failure rate is constructed out-of-sample using an expanding sample that only incorporates information up to year $t - 1$. The predicted failure rate in panel A is based on the models in columns (1) through (4) of Table 1. Panel B uses a logit model with the same predictors as in column (4) of Table 1 on various time samples. Panel C uses a linear probability model with richer period-specific models from column (4) of Table B.5, Table B.8, Table B.9, and Table B.10. Newey-West standard errors in parentheses with truncation parameter $S = 1.3T^{1/2}$ following Lazarus et al. (2018). *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table B.17: Asset Recovery Rates and Pre-Failure Market Structure and Receivership Length

Dependent variable	Recovery Rate						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
2 banks in market before failure	-1.90** (0.80)	-3.38*** (0.77)	-1.24* (0.72)				
3 banks	-3.34*** (1.28)	-5.61*** (1.24)	-1.98* (1.18)				
4 or more banks	-3.27*** (1.20)	-8.91*** (1.24)	-3.70*** (1.24)				
Receivership length (in years)				-0.51*** (0.12)	0.11 (0.11)	-0.78*** (0.12)	-0.15 (0.11)
Loans/assets		-27.74*** (2.01)	-17.77*** (2.02)			-27.96*** (2.05)	-17.60*** (2.06)
Surplus/equity		7.84*** (2.00)	6.33*** (1.84)			11.21*** (2.01)	8.29*** (1.87)
Size (log/assets))		3.01*** (0.35)	1.76*** (0.34)			2.52*** (0.37)	1.73*** (0.34)
N	2717	2708	2704	2502	2498	2494	2490
R ²	0.006	0.129	0.313	0.007	0.272	0.131	0.316
Year FE			✓		✓		✓

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

$$\text{Recovery Rate}_b = \tau_t + \beta X_b + \epsilon_b,$$

where the Recovery Rate_b is calculated as the ratio of the total funds collected in receivership over total assets held at suspension and additional assets received throughout receivership, τ_t is a set of year fixed effects, and X_b is a set of bank characteristics observed either before or in receivership. X_b is either the number of banks active in the market before failure or the length of the receivership (in years) or balance sheet characteristics from before receivership (such as size measured in log of nominal assets or capitalization and loan ratio). *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table B.18: Loss Rates for Uninsured Depositors in Bank Failures: Pre-FDIC versus Post-FDIC

Era	Number of failures	Share of failures with losses to depositors	Conditional loss rate	Unconditional loss rate
Panel A: Pre-FDIC				
1863-1913 (NB Era)	533	0.68	0.39	0.27
1914-1918 (Early Fed)	732	0.91	0.52	0.47
1929-1933 (Depr., pre-Holiday)	1031	0.90	0.43	0.39
1933-1934 (Depr., post-Holiday)	605	0.65	0.28	0.18
All	2901	0.81	0.42	0.34
Panel B: Post-FDIC				
1992-2007	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 loss rates reported in panel (A) are from the OCC’s tables on national banks placed in receivership. The final loss rate for depositors does not account for interest payments or discounting. The data in panel (B) are as reported in FDIC (2023). The conditional loss rate is the loss rate for failures involving a loss for uninsured depositors.

Table B.19: Share of Fundamentally Insolvent Banks by ρ and v for Failures With and Without Runs

ρ	$v = 0$	$v = 2.5\%$	$v = 5\%$	$v = 7.5\%$	$v = 10\%$	$v = 15\%$	$v = 20\%$
Panel A: Failures with run (net deposit outflow larger than 7.5%)							
0%	0.88	0.86	0.84	0.82	0.79	0.73	0.66
5%	0.84	0.82	0.79	0.75	0.72	0.65	0.58
10%	0.78	0.74	0.71	0.67	0.63	0.57	0.51
20%	0.59	0.56	0.53	0.50	0.48	0.43	0.37
Panel B: Failures without run (net deposit outflow less than 7.5%)							
0%	0.77	0.72	0.69	0.64	0.59	0.52	0.45
5%	0.68	0.63	0.58	0.55	0.51	0.44	0.39
10%	0.57	0.54	0.50	0.46	0.43	0.38	0.34
20%	0.40	0.38	0.35	0.33	0.31	0.27	0.23

Notes: This table is similar to Table 7, but we report the share of banks for which the insolvency condition holds separately for banks with net deposit outflows above and below 7.5%. The calculations are based on the sample of banks for which deposits at suspension are reported by the OCC.

Table B.20: Sensitivity of the Share of Fundamentally Insolvent Banks to Recovery Rate Calculations

ρ	$v = 0$	$v = 2.5\%$	$v = 5\%$	$v = 7.5\%$	$v = 10\%$	$v = 15\%$	$v = 20\%$
Panel A: Double liability							
0%	0.67	0.64	0.61	0.58	0.54	0.48	0.43
5%	0.61	0.57	0.54	0.50	0.48	0.42	0.37
10%	0.53	0.49	0.47	0.44	0.41	0.36	0.32
20%	0.38	0.36	0.33	0.31	0.29	0.25	0.22
Panel B: Deposits at suspension							
0%	0.86	0.84	0.82	0.80	0.77	0.72	0.67
5%	0.82	0.79	0.77	0.74	0.71	0.66	0.59
10%	0.76	0.73	0.70	0.67	0.64	0.58	0.52
20%	0.61	0.57	0.54	0.51	0.48	0.42	0.36

Notes: This table reports the share of banks that are fundamentally insolvent defined as

$$\frac{1}{N} \sum_b \mathbb{I} \left[\frac{1+v}{1-\rho} < \frac{\ell_b}{R_b} \right].$$

In both panels, the calculations are based on a sample of all national banks placed into the hands of a receiver from 1863 through 1934. In Panel A, we construct the recovery rate R by dividing all funds recovered by the receiver—from the failed banks' assets as well as from shareholders due to their double liability—against the sum of assets held at suspension plus additional assets collected during the receivership. In Panel B, we calculate the leverage ratio ℓ by using the sum of deposits at suspension, offsets, and other liabilities (as opposed to proven claims, offsets, and other liabilities).

Table B.21: Duration of Receiverships, 1863-1941

Length of receivership (in years)				Share of receiverships by length					
Average	Median	p25	p75	<1 year	1-2 years	2-4 years	4-8 years	8-16 years	>16 years
5.8	6	4	7	.054	.041	.18	.51	.097	.02

Notes: This table shows the distribution of the number of days elapsed between the date a receiver was appointed and the date on which the receivership was closed, for all receiverships started between 1863 and 1934 that were already closed by 1941.

C Data Appendix

C.1 Appendix B1: Call Reports

OCC Annual Report to Congress: 1863 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. 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 become first available in 1863. [Figure C.1](#) shows an example of a balance sheet from the report from 1900. Until 1904, the report has up to three balance sheets on one page, each as its own table. These data have been digitized by Carlson et al. (2022) and made available online.

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

To construct the panel, we compile a list of all significant bank events and their dates. Events include chartering, liquidations, and receiverships. The list of events is based on data manually collected by van Belkum (1968), augmented by Huntoon (2023), and which we validate by 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.

Figure C.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's house, furniture, and fixtures	1,000.00	Due to trust companies and sav- ings 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 C.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

ILLINOIS—Continued
DISTRICT NO. 8—Continued

	Location and name of bank	President	Cashier	Loans and discounts, including overdrafts	United States Government securities owned	Other bonds, stocks, and securities, etc., owned
1	National City, National Stock Yards	O. J. Sullivan	R. D. Garvin	\$3,664,800	\$6,532,834	\$733,004
2	New Douglas, Prange	A. F. Prange	W. W. Prange	107,457	50,000	64,239
3	Oblong, First	S. F. Odell	J. B. McKnight	786,318	83,500	208,704
4	O'Fallon, First	E. H. Sniley	W. R. Dorris	296,662	174,207	484,832
5	Okawville, First	W. G. Frank	W. E. Friend	151,768	79,547	307,394
6	Okawville, Old Exchange	C. H. Merrick	F. Moehle	88,300	76,675	216,049
7	Pittsfield, First	L. C. King	F. A. Hicks	650,876	251,425	166,315
8	Ramsey, Ramsey	L. C. Thiele	J. E. Easterday	137,655	51,250	43,077
9	Raymond, First	J. E. McDavid	C. McNaughton	431,989	35,588	116,639
10	Robinson, Second	A. U. McCandless	A. H. Lodge	1,190,820	485,556	327,905
11	St. Francisville, Peoples	S. Gray	G. H. Corrie	170,068	107,500	110,128
12	Salem, Salem	J. C. Martin	A. H. Bachman	353,021	968,786	1,324,844
13	Sandoval, First	B. F. Holmes	H. H. Bellamy	58,831	45,710	28,768
14	Smithton, First	J. A. Miller	E. P. Baltz	113,288	59,881	80,845
15	Sorento, National	L. C. Dreiling	H. H. Holbrook	10,902		9,491
16	Sparta, First	T. B. Stephenson	P. G. Brown	168,354	95,550	53,236
17	Stanton, Stanton	C. F. Hackman	J. W. P. Kerr	85,469	82,293	237,000
18	Sumner, First	G. W. Hill	O. D. Atkins	38,933	59,787	148,707
19	Vandalia, First	F. L. Rice	R. H. Sturress	234,469	428,738	170,332
20	Vienna, First	W. L. Williams	F. E. Worrell	213,432	100,181	33,951
21	Waterloo, First	N. B. Pautler	J. F. Schmidt	172,706	223,338	136,773
22	Wayne City, First	J. F. Mateer	W. O. Allen	88,400	52,700	33,908
23	White Hall, White Hall	C. A. Ruckel	R. S. Worcester	371,118	206,063	188,280
24	Witt, Security	H. F. Fesser	H. S. Armentrout	121,245	64,346	138,243
25	Woodlawn, First	E. A. Hill	M. Wood	68,828	47,822	44,461
26	Wood River, First	O. F. Nagel	G. G. Guker	237,024	92,269	170,906
27	Wood River, Wood River	J. M. Olin	H. E. Paton	261,407		53,577
28	Worden, First	T. C. Unger	W. E. Meyer	38,797	33,308	10,941
29	Xenia, First	J. M. Tully	E. Kepp	99,489	34,000	1,169
30	Zeigler, First	F. G. Hiitt	R. R. Frazier	49,690	396,574	230,202

Cash and exchange including reserve with Federal Reserve bank	Other assets	Total assets	Capital	Surplus	Undivided profits	Total deposits	Circulation	Bills payable and rediscounts	Other liabilities
\$3,678,840	\$123,007	\$14,732,491	\$750,000	\$150,000	\$45,440	\$12,983,612	\$750,000		\$53,439
16,019	4,386	242,081	25,000	10,000	837	206,244			
210,440	76,380	1,365,342	75,000	50,000	21,563	1,144,859	73,860		
183,751	75,195	1,214,647	100,000	30,000	4,676	979,939	100,000		
44,503	5,173	588,375	50,000	10,000	7,526	470,830	50,000		
67,929	4,889	453,842	50,000	10,000	14,951	328,891	50,000		
206,835	113,931	1,389,382	125,000	125,000	41,325	998,602	99,280		
68,692	14,762	315,436	25,000	25,000	7,675	232,761	25,000		
34,659	41,646	660,541	50,000	10,000	763	494,282	25,000	\$80,496	
432,586	67,348	2,504,215	150,000	37,500	33,989	2,188,976	93,750		
34,200	19,456	441,352	70,000	10,000	5,723	305,624	50,000		
360,591	71,420	3,078,662	100,000	24,000	56,830	2,822,645	75,000		
49,091	24,437	206,837	40,000	2,500	1,301	138,354	24,640		
25,757	16,668	296,439	25,000	8,000	350	238,032	25,000		
30,302	5,532	56,227	25,000	1,850	(d) 7,631	33,982		3,000	
178,157	30,215	525,512	50,000	25,000	11,078	389,401	50,000		
64,862	15,841	455,465	50,000	10,000	26,387	349,632	50,000		
81,973	8,685	333,085	25,000	5,000	674	281,707	25,000		
202,289	68,789	1,104,597	100,000	25,000	19,369	886,078	100,000		
57,696	39,123	464,383	60,000	25,000	2,812	317,130	39,340		
100,669	6,356	639,872	25,000	15,000	1,437	573,435	25,000		
35,121	33,126	243,255	45,000		1,436	171,768	25,000		
121,473	16,158	963,112	100,000	20,000	29,480	703,632	50,000		
27,991	7,947	359,572	25,000	5,000	5,248	299,124	25,000		
95,669	9,520	265,000	35,000	2,000	3,282	209,718	25,000		
123,661	50,285	674,145	50,000	50,000	2,571	521,416	50,000		
129,894	69,034	315,912	60,000	30,000	10,786	415,126			
18,348	11,710	113,104	25,000	5,000	194	57,912	24,998		
82,560	14,866	202,084	25,000		1,082	150,963	23,000		
116,201	46,553	829,220	35,000	7,000	23,940	729,280	34,000		

C.1.1 FFIEC Reports of Condition and Income: 1959 through 2024

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 bi-annual and since 1974 quarterly information on balance sheets and income statements on a consolidated basis for all commercial banks operating in the United States and regulated by the FRS, the FDIC, and the OCC.

We construct the data using the following FFIEC forms:

- FFIEC 010: Domestic Report of Condition (< \$100 million in Total Assets). It was filed from June 10, 1959 to December 31, 1983. Prior to December 31, 1960, this was reported by FRS member banks and a handful of nonmember banks. Afterwards, it was reported by all insured commercial banks, savings banks, nondeposit trust companies, and industrial banks with domestic offices only. From December 31, 1978 to December 31, 1983, it was reported by all banks with domestic offices only with less than \$100 million in total assets. From 1964 to 1972, data is reported semiannually. Otherwise, data is reported quarterly. [Figure C.3](#) shows an example of the historical balance sheet reporting form used in 1967.
- FFIEC 011: Consolidated Report of Income (< \$100 million in Total Assets). It was filed from December 31, 1960 to December 31, 1983 by all insured commercial banks, savings banks, nondeposit trust companies, and industrial banks. From December 31, 1978 to December 31, 1983, it was reported by all banks with less than \$100 million in total assets. From 1960 to 1975, data is reported annually at the end of Q4. From 1976 to 1982, data is reported semiannually in Q2 and Q4 for savings banks and nondeposit trust companies. Otherwise, data is reported quarterly on a year-to-date basis. [Figure C.4](#) shows an example of the income statement reporting form from 1967.
- FFIEC 012: Consolidated Report of Condition for a Bank and its Domestic Subsidiaries (Domestic Offices Only). It was filed from December 31, 1978 to December 31, 1983. It was reported by all insured commercial banks, savings banks, nondeposit trust companies, and industrial banks with domestic offices only. Data is reported quarterly.
- FFIEC 013: Consolidated Report of Income for a Bank and its Domestic and Foreign Subsidiaries. It was filed from December 31, 1978 to December 31, 1983 by all insured commercial banks, savings banks, nondeposit trust companies, and industrial banks with domestic offices and foreign branches, foreign subsidiaries, Edge Act and agreement subsidiaries, and/or branches in Puerto Rico or U.S. territories and possessions. From 1978 to 1982, data is reported semiannually in Q2 and Q4 for savings banks and nondeposit trust companies. Otherwise, data is reported quarterly on a year-to-date basis.
- FFIEC 014: Consolidated Report of Condition for a Bank and its Domestic and Foreign Subsidiaries. It was filed from June 30, 1969 to December 31, 1983. This

form was filed by all insured commercial banks with domestic offices and foreign branches, foreign subsidiaries, Edge Act and agreement subsidiaries, and/or branches in Puerto Rico or U.S. territories and possessions. Prior to 1974, the respondent panel consisted of member banks of the Federal Reserve System with domestic and foreign offices. Prior to 1976, foreign holdings were reported semiannually during the June/December reports. Otherwise, data is reported quarterly.

- FFIEC 031: Consolidated Reports of Condition and Income for a Bank with Domestic and Foreign Offices. It has been filed since March 31, 1984 to present. It is filed by all national banks, state member banks, insured state nonmember banks, and savings associations with branches or consolidated subsidiaries in a foreign country, Puerto Rico, or a U.S. territory or possession, or have international banking facilities. As of June 30, 2018, it is also filed by banks with domestic offices only, if they have total consolidated assets of \$100 billion or more. Additionally, as of March 2020 banks with domestic offices only are required to file this form if they are an advanced approaches institution. Data is reported quarterly.
- FFIEC 032: Consolidated Reports of Condition and Income for a Bank with Domestic Offices Only and Total Assets of \$300 Million or More. It was filed from March 31, 1984 to December 31, 2000. It was filed by all national banks, state member banks, and insured state nonmember banks with domestic offices only and total assets of \$300 million or more. Data is reported quarterly.
- FFIEC 033: Consolidated Reports of Condition and Income for a Bank with Domestic Offices Only and Total Assets of \$100 Million or More But Less Than \$300 Million. It was filed from March 31, 1984 to December 31, 2000. It was filed by all national banks, state member banks, and insured state nonmember banks with domestic offices only and total assets of \$100 million or more, but less than \$300 million. Data is reported quarterly.
- FFIEC 034: Consolidated Reports of Condition and Income for a Bank with Domestic Offices Only and Total Assets Less Than \$100 Million. It was filed from March 31, 1984 to December 31, 2000. It was filed by all national banks, state member banks, and insured state nonmember banks with domestic offices only and total assets less than \$100 million. Data is reported quarterly.
- FFIEC 041: Consolidated Reports of Condition and Income for a Bank with Domestic Offices Only. It has been filed since March 31, 2001 to present. It replaced the FFIEC 032, FFIEC 033, and FFIEC 034 forms. It is filed by all national banks, state member banks, insured state nonmember banks, and savings associations with domestic offices only. Data is reported quarterly.
- FFIEC 051: Consolidated Reports of Condition and Income for a Bank with Domestic Offices Only and Total Assets Less than \$5 Billion. It has been filed since March 31, 2017 to present. From March 31, 2017 to June 30, 2019 it was filed by all national banks, state member banks, insured state nonmember banks, and savings associations with domestic offices only and total assets less than \$1 billion. From

Table C.1: Definitions of variables cased on call report 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	1976-03-31 to 2000-12-31
		+1757	
		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	RIAD	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

September 30, 2019 to present, it is filed by all national banks, state member banks, insured state nonmember banks, and savings associations with domestic offices only and total assets less than \$5 billion. Note that while some banks may fall under these criteria, they may elect to file the FFIEC 041 or be required to for regulatory capital purposes or as instructed by their primary federal regulator. Data is reported quarterly.

We document the construction of the variables from line items in table [Table C.1](#).

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

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

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				
13. Demand deposits of individuals, partnerships, and corporations (Schedule E, item 4).....	2615	2220		13
14. Time and savings deposits of individuals, partnerships, and corporations (Schedule F, item 6).....		2360		14
15. Deposits of United States Government (Schedule E, item 5 and Schedule F, item 7).....		2610		15
16. Deposits of States and political subdivisions (Schedule E, item 6 and Schedule F, item 8).....		2620		16
17. Deposits of foreign governments and official institutions, central banks and international institutions (Schedule E, item 7 and Schedule F, item 9).....		2650		17
18. Deposits of commercial banks (Schedule E, items 8 and 9 and Schedule F, items 10 and 11).....	2645	2660		18
19. Certified and officers' checks, etc. (Schedule E, item 10).....		2330		19
20. TOTAL DEPOSITS (items 13 to 19).....	\$ 2200	xxx xxx xxx xx		20
(a) Total demand deposits (Schedule E, item 11).....	\$ 2210	xxx xxx xxx xx		(a)
(b) Total time and savings deposits (Schedule F, item 12).....	\$ 2350	xxx xxx xxx xx		(b)
21. Federal funds purchased and securities sold under agreements to repurchase.....		2800		21
22. Other liabilities for borrowed money.....		2850		22
23. Acceptances executed by or for account of this bank and outstanding.....	2915	2920		23
24. Other liabilities (item 7 of "Other liabilities" schedule) (including \$..... mortgages and other liens on bank premises and other real estate).....		2930		24
25. TOTAL LIABILITIES.....		2950		25
CAPITAL ACCOUNTS				
26. (a) Capital notes and debentures.....		3200		26 (a)
(b) Preferred stock—total par value.....		3220		(b)
(No. shares outstanding.....)				
(c) Common stock—total par value.....		3230		(c)
(No. shares authorized.....)				
(No. shares outstanding.....)	3210			
27. Surplus.....		3240		27
28. Undivided profits.....		3250		28
29. Reserve for contingencies and other capital reserves.....		3260	3247	29
30. TOTAL CAPITAL ACCOUNTS.....		3270		30
31. TOTAL LIABILITIES AND CAPITAL ACCOUNTS.....		3300		31

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

		December 31, 1978 - December 31, 1982		RCRI
Consolidated Report of Income of _____		Legal Title of Bank		RTAD
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	4189	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.

C.2 Data on National Bank Receiverships

We digitize an extensive set of tables with information on national banks in charge of receivers from the OCC's Annual Report to Congress from each year between 1920 to 1941. The 1920 OCC Annual Report contains information on all receiverships from the first receivership in 1865 until receiverships initiated in August 1920. We further digitize the tables on receiverships for each year from 1921 to 1941 to record information on receiverships initiated after 1920, as well as receiverships initiated before 1920 but terminated after 1920.

These data contain a range of information, including the date the receiver was appointed; the date the bank was finally closed; deposits at suspension; assets at suspension; an estimate of the breakdown of assets at suspension by good, doubtful, or worthless assets; additional assets received after the date of suspension; total collections from assets; total collections from shareholder assessments; dividends paid to claim holders; amount of claims proved; secured and preferred liabilities paid; and legal expenses. The data on deposits outstanding at the time of suspension are available starting in 1880. These tables also contain the OCC's assessment of the cause of failure. We harmonize variable definitions over time, as some variable definitions are subject to change. For example, from 1927 onwards, secured and preferred liabilities paid includes offsets allowed and settled, but it excludes offsets before 1927.

We calculate three main statistics from the receivership data.

- **Recovery Rate, R :** We calculate the recovery rate R as the amount "collected from assets" divided by the sum of "nominal assets at date of suspension" and "additional assets received since date of suspension".
- **Total Liabilities at Failure, D ,** we calculate D as the "amount of claims proved" (which refers to claims held by depositors, including unsecured interbank deposits) plus "offsets allowed and settled" and "Loans paid and other disbursements" (which in later years is reported as "secured and preferred liabilities paid except through dividend, including offsets" and includes secured claims such as other borrowed money or bills payable and rediscounts) paid out at failure. We proxy secured and preferred liabilities at failure by the total effective payments made to these types of claims throughout the receivership. Hence, we implicitly assume full recovery rate for non-deposit liabilities. While we have no information on the actual recovery rates of these types of liabilities, observe that if the effective recovery rate were less than 1, we would be underestimating total liabilities at failure. Underestimating total liabilities, in turn, implies that the share of fundamentally insolvent banks is even higher than estimated.
- **Deposit Recovery:** For the depositor recovery rate, we use the dividends paid (in %), reported by the OCC. This reflects the dividends paid relative to the amount of claims proved. The depositor recovery rate does not include interest or account for the time value of money. [Figure B.10](#) shows that the depositor recovery in the first year amounts to only about half of the final recovery.

To ensure robustness, we also study the sensitivity of our findings to calculating the solvency ratio in [Equation \(3\)](#) in different ways. In our baseline approach, we use the sum of collected from assets and offsets allowed and settled, divided by the sum of the amount of claims proved, secured and preferred liabilities paid, and offsets allowed and settled. We also consider two alternative approaches. First, we calculate the denominator as deposits at suspension, secured and preferred liabilities paid, and offsets allowed and settled. Second, we calculate the numerator as sum of collected from assets, offsets allowed and settled, and collected from shareholders. [Table B.20](#) shows the share of fundamentally insolvent banks when using these alternative ways of constructing the solvency ratio.

C.2.1 Causes of Failures as Classified By the OCC

From 1863 to 1928, the OCC classified the “apparent cause of failure” for almost all bank failures. For 1929, 1930, and 1931, the OCC classified the cause of failure for 78%, 75%, and 48% of failures, respectively. The OCC did not classify the cause of failure for failures occurring in 1932 and 1933. However, we were able to obtain the cause of failure for 12 failures from 1934-1937 from the OCC’s 1937 Annual Report to Congress. See [Figure C.5](#) for the share of failures not classified by year.

We group the detailed cause of failure classifications from the OCC into one of 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.
- **Economic conditions:** We classify failure as caused by external economic 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.

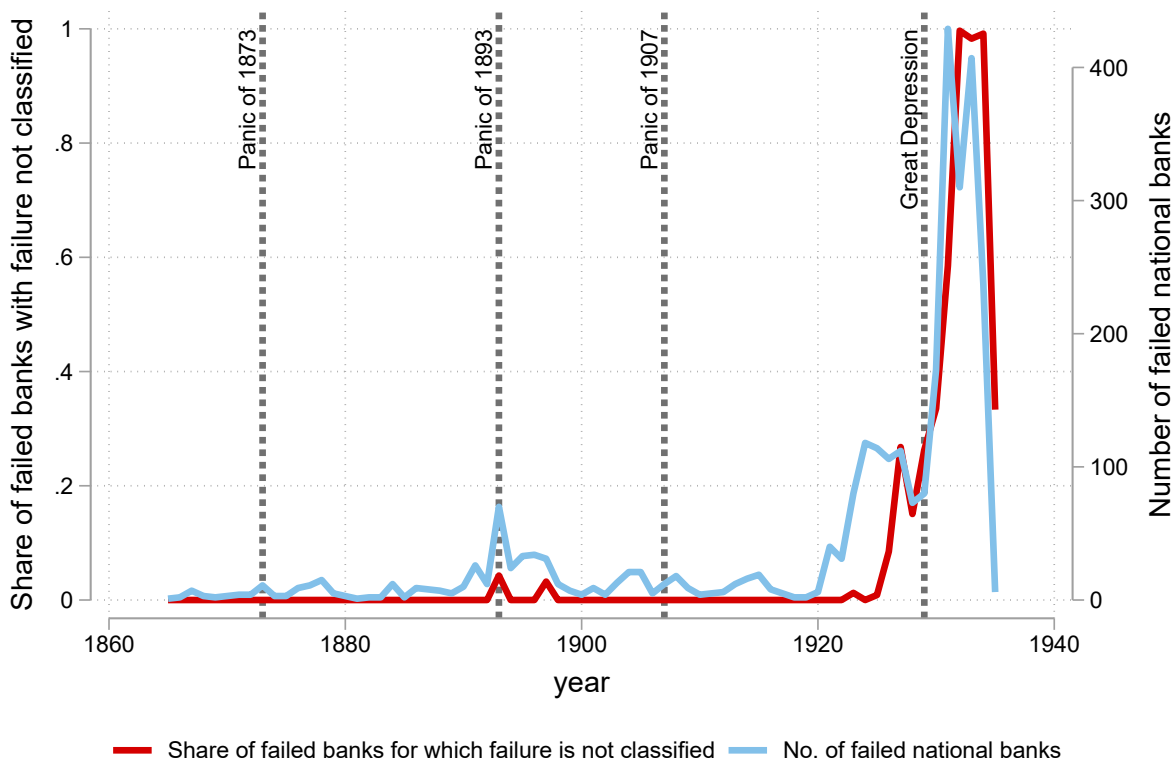
[Table C.2](#) shows the detailed mapping to these categories.

Relation to the literature. Calomiris and Gorton (1991) analyzes the cause of failure from this same source, but they 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).

Using classifications from the Federal Reserve Board of Governors, Richardson (2007) finds that, for the period 1929 through 1933, the main cause of failure of Federal Reserve member banks was asset losses, but illiquidity from heavy withdrawals also played a contributing role. The evidence from the historical sample is also consistent with a detailed study conducted by the OCC of 171 bank failures between 1979 and 1987 (Graham and Horner, 1988). That study argued that the “major cause of decline for problem banks continues to be poor asset quality that eventually erodes a bank’s capital.” 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.”

Poor asset quality was most often caused by poor management decisions and practices, such as imprudent lending practices, excessive loan growth, and fraud. For instance, Bennett and Unal (2015) find that fraud was a primary or contributing cause of failure in 24% of failures based on a sample of failures between 1989 and 2007.

Figure C.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 did not provide a cause of failure (left y-axis) and the number of failed national banks (right y-axis) from 1863 through 1935.

Table C.2: OCC Causes of Failure Classification.

<i>OCC Cause of Failure</i>	<i>Simplified Label</i>
Crop loss and depreciation of securities	Economic conditions
Crop loss	Economic conditions
Deflation	Economic conditions
Local financial conditions	Economic conditions
Local financial depression from unforeseen agricultural or industrial disaster	Economic conditions
Excessive loans and failure of large debtors	Excessive lending
Excessive loans to officers and directors	Excessive lending
Excessive loans to others and depreciation of securities	Excessive lending
Excessive loans to others and investments in real estate and mortgages	Excessive lending
Excessive loans to others, injudicious banking, and depreciation of securities	Excessive lending
Excessive loans	Excessive lending
Failure of large debtors	Excessive lending
Defalcation by cashier	Fraud
Defalcation by former cashier	Fraud
Defalcation of officers and depreciation of securities	Fraud
Defalcation of officers and excessive loans to others	Fraud
Defalcation of officers and fraudulent management	Fraud
Defalcation of officers	Fraud
Dishonesty of an officer of employee and local financial depression from unforeseen agricultural or industrial disaster	Fraud
Dishonesty of an officer of employee	Fraud
Dishonesty	Fraud
Excessive loans to officers and directors and depreciation of securities	Fraud
Excessive loans to officers and directors and investments in real estate and mortgages	Fraud
Forgeries and embezzlement	Fraud
Fraudulent management	Fraud
Fraudulent management and closed by run	Fraud
Fraudulent management and depreciation of securities	Fraud
Fraudulent management and injudicious banking	Fraud
Fraudulent management and local financial conditions	Fraud
Fraudulent management, defalcation of officers, and depreciation of securities	Fraud
Fraudulent management, excessive loans to officers and directors, and depreciation of securities	Fraud
Fraudulent management, excessive loans to officers and directors, and excessive loans to others	Fraud
Fraudulent management, injudicious banking, investments in real estate and mortgages, and depreciation of securities	Fraud
Fraudulent management	Fraud

Irregularities of president and speculation in real estate	Fraud
Irregularities	Fraud
Wrecked by assistant cashier	Fraud
Wrecked by cashier and president and by excessive loans to themselves	Fraud
Wrecked by defalcation by bookkeeper	Fraud
Wrecked by president	Fraud
Wrecked by the cashier	Fraud
Bad management	Governance
Incompetent management and dishonesty of an officer of employee	Governance
Incompetent management and local financial depression from unforeseen agricultural or industrial disaster	Governance
Incompetent management	Governance
Bad paper taken over from old organization	Losses
Bad paper	Losses
Deficient reserve and unable to realize on loans	Losses
Depleted reserve	Losses
Depleted reserve and shrinkage of deposits	Losses
Depreciation of securities	Losses
Formerly in voluntary liquidation	Losses
General stringency of the money market, shrinkage in values, and imprudent methods of banking	Losses
Injudicious banking and adverse business conditions	Losses
Injudicious banking and depreciation of securities	Losses
Injudicious banking and excessive loans to officers and others	Losses
Injudicious banking and failure of large debtors	Losses
Injudicious banking	Losses
Insufficient credit	Losses
Investment in real estate mortgages and depreciation of securities	Losses
Investments in real estate and mortgages and depreciation of securities	Losses
Large losses and defalcation	Losses
Large losses and injudicious banking	Losses
Large losses in loans and discounts	Losses
Large losses, withdrawals, and insufficient credit	Losses
Large losses	Losses
Receiver appointed after sale of assets, and stockholders to vote to place bank in liquidation	Losses
Receiver appointed after voluntary liquidation	Losses
Receiver appointed to assess stockholders	Losses
Receiver appointed to levy and collect stock assessment covering deficiency in value of assets sold, or to complete unfinished liquidation	Losses
Receiver appointed to levy and collect stock assessment covering deficiency in value of assets sold	Losses
Unable to realize on assets	Losses
Unable to realize on loans and failure of stockholders to pay balance due on capital	Losses

Unable to realize on loans	Losses
Information not available	No information
Robbery and burning of bank	Other
Temporary suspension	Other
Temporary suspension to adjust settlement on adverse judgment	Other
Closed by directors in anticipation of run	Run
Closed by run	Run
Directors closed due to rumor of run	Run
Heavy withdrawals and lack of public confidence	Run
Heavy withdrawals	Run
Inability to meet demands	Run
Large demands and depleted cash	Run
Local financial conditions and closed by run	Run