Bank Runs: Causes and Consequences

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Abstract

We apply natural language processing to historical newspapers to study episodes of bank distress involving bank runs, suspensions, and failures in the United States from 1863 to 1934. We identify 4,334 runs, 15,661 suspensions, and 12,782 failures in newspaper accounts. We merge these distress episodes to data on national bank financial statements and failures. We present five findings. First, runs without failure were common before deposit insurance. Second, runs are considerably more likely in weak banks, but they also happen in strong banks. Third, runs usually only result in failure for banks with weak fundamentals. Fourth, runs without failure are associated with bank-level deposit and lending contractions, especially for banks with weak fundamentals. Finally, at the local level, bank failures (with and without runs) translate into substantially larger local declines in deposits and lending than runs without failures. Our findings suggest that poor bank fundamentals are necessary for bank runs to translate into failure and, more broadly, for bank distress to translate into severe economic consequences.

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1 Introduction

This paper uses novel microdata on bank runs in the U.S. from 1863 to 1934 to study their causes and consequences. We address the following questions: Which banks are subject to runs? When do bank runs result in bank failure? Can runs trigger the failure of healthy banks? And what are the consequences of bank runs with and without failures for lending and the real economy?

Bank runs are a salient feature of many financial crises. Banks finance illiquid assets with demandable liabilities, making them vulnerable to a sudden withdrawal of funding by creditors (Diamond and Dybvig, 1983). There remain a range of perspectives on the causes of runs and their role in understanding the severe consequences of financial crises. One perspective sees runs as the key turning point in financial crises and that accounts for their severe consequences (Gorton, 2012; Bernanke, 2018). A related perspective sees runs as important amplification mechanism of poor fundamentals (Goldstein and Pauzner, 2005; Gertler and Kiyotaki, 2015). Another perspective argues that runs are usually a consequence of deeper fundamental problems in the banking system that are the root cause of severe financial crises (Gennaioli and Shleifer, 2018; Correia et al., 2025; Baron et al., 2025).

A challenge for understanding the causes of runs and their consequences is the absence of systematic data on the occurrence of bank runs, especially runs that do not result in bank failure. Existing micro-level studies of bank distress typically focus on bank failures, as these are objectively recorded in historical records (Calomiris and Mason, 2003; Martin et al., 2023; Blickle et al., 2024). However, this misses the broader universe of runs that did not involve failure. At the same time, studies of bank runs typically focus on granular data from specific episodes (Iyer and Puri, 2012; Iyer et al., 2016; Cipriani et al., 2024) or consider aggregate data on banking panics (Calomiris and Gorton, 1991; Baron et al., 2021; Jamilov et al., 2024).

We overcome this gap of a lack of large-scale bank-level evidence on bank runs by applying natural language processing to historical newspapers to create a new database of bank distress episodes. Our final data comprises around 55,000 bank-specific distress events, distinguishing between bank runs, suspensions, and failures. We then identify around 25,000 bank-specific distress episodes in which the same bank is subject to one or more distress events within the same time period. Distress episodes are thus combinations of distress events such as bank runs that result in suspension and failure, bank runs that result in temporary suspension but not failure, or bank runs that have no consequences. The data collection effort allows us to create a comprehensive database of all bank distress

episodes recorded in newspaper accounts before the introduction of deposit insurance. We further merge these data on bank distress episodes with data on bank balance sheets and failures for national banks using information from Correia et al. (2025), allowing us to study the relation between bank balance sheets and the incidence of bank runs and bank failures.

Our analysis focuses on the U.S. banking system from 1863 to 1934. This sample provides an appealing setting to understand the drivers and consequences of runs. Bank runs rarely occur in contemporary banking systems due to a wide variety of government interventions that affect depositor behavior, such as deposit insurance (Iyer et al., 2019) and lending of last resort (Metrick and Schmelzing, 2021). However, government interventions in the financial sector were more limited before the Great Depression and the introduction of federal deposit insurance in 1934, making runs much more common in this time period.

We start by presenting our novel database of bank distress episodes. Focusing on the sample from 1863 to 1934, we identify 4,334 runs, 15,661 suspensions, and 12,782 failures. We validate our bank distress episodes database by showing that spikes in the rate of bank distress episodes line up closely with existing narrative chronologies of banking crises in the United States, both at the aggregate and regional level. We also show that newspaper accounts of national bank failures are strongly correlated with the true rate of national bank receiverships. Moreover, national bank failures that our new database classifies as involving runs involve a 10 percentage point larger deposit outflow right before failure.

Our first finding is to establish that many bank runs are not associated with bank failure. We find that roughly 37% of runs are associated with a bank failure, while 63% do not result in failure. Runs without failure are not captured in studies of bank distress focusing on bank failures. Further, we find that about 31% of the runs that do not result in failure nevertheless lead to a temporary suspension of convertibility. Suspension was thus a common way to successfully resolve runs.

Which banks are subject to runs? We establish that runs are more likely to occur in banks with weak observable fundamentals. We measure fundamentals using balance sheet measures capturing bank capitalization and the ability of a bank to finance itself with cheap deposits relative to expensive noncore funding. Existing research shows that these metrics capture bank health and failure risk (White, 1984; Calomiris and Mason, 2003; Correia et al., 2025). We document that a run is about five times more likely for a bank in the lowest decile of fundamentals relative to a bank in the highest decile. At the same time, while less common, even the strongest banks can be subject to runs. Runs on strong banks can occur, for instance, due to unfounded rumors or during an aggregate

panic.

What determines whether a run results in bank failure? Runs are significantly more likely to result in failure for banks with weak fundamentals. Conditional on a run, a bank in the lowest decile of fundamentals has a nearly 70% probability of failing. In contrast, runs on strong banks almost never result in failure. Thus, weak fundamentals are necessary for a run to lead to bank failure. Consistent with this, we observe significant differences in bank health across banks that survive runs compared to banks that fail from runs. This aligns with previous evidence that bank failures are strongly linked to weak bank fundamentals (Correia et al., 2025). This collection of evidence implies that failures are strongly predictable based on bank fundamentals, runs are moderately predictable, but runs without failure are essentially unpredictable.

Focusing on banks that fail, we find that banks that fail with and without a run follow a similar deterioration in fundamentals. Interestingly, banks that fail with a run do not have stronger fundamentals on the margin compared to banks that fail without a run. This suggests that runs, on average, do not cause failure of relatively healthier banks. Instead, the run was the immediate trigger of failure for weak banks that likely would have failed absent the run. This finding echoes Calomiris and Mason (1997), who find that bank failures during the Chicago Panic in the Great Depression followed a similar deterioration of fundamentals as banks that failed outside of the panic.

The finding that runs can occur for both weak and strong banks, but that only weak banks fail from runs, has important implications for theories of bank runs. The evidence is broadly consistent with asymmetric information theories of bank runs, where depositor confusion leads to withdrawals from both weak and strong banks because depositors struggle to distinguish which banks are solvent (Gorton, 1988; Chari and Jagannathan, 1988; Calomiris and Gorton, 1991). At the same time, our finding that weak and strong banks can be separated based on simple publicly available balance sheet metrics suggests some limits to rationality on the part of depositors. This is perhaps not surprising in a context where most depositors had limited financial literacy and likely could not conduct a meaningful financial analysis of bank health easily. Moreover, the fact that only weak banks fail with runs is consistent with theories emphasizing that suspension of convertibility, interbank borrowing, and other mechanisms can prevent runs from translating into failure of solvent banks (Gorton, 1985). This finding is not consistent with the notion that nonfundamental runs can cause failures of otherwise healthy banks, as in Diamond and Dybvig (1983) and related models. Furthermore, the fact that runs trigger failure of weak banks is broadly consistent with both models of fundamental-based panic runs (Morris and Shin, 2000; Goldstein and Pauzner, 2005). However, in models

of fundamental-based panic runs, runs do not occur on strong banks unless there is substantial noise in depositor signals about fundamentals.

We next study the consequences of runs and failures at the bank and local level. We first focus on the bank-level consequences of runs for banks that survive runs. Banks that are subject to runs and survive see a sharp contraction in deposits and loans of about 7.5%. The contraction is persistent, lasting for over four years. We then distinguish between episodes with only a run and episodes with a run, suspension, and reopening. "Run only" episodes lead to smaller declines in deposits, followed by a full recovery, while "run-suspension-reopenings" lead to larger and more persistent deposit contractions. Further, we find that the bank-level deposit and lending contractions following runs are much stronger for banks with *ex ante* weak fundamentals. Thus, fundamentals shape the severity of the consequences of runs, even when runs do not translate into failure.

We conclude by studying the consequences of bank runs and failures for local deposits and lending. We use the richness of our bank distress episodes data to consider three mutually exclusive types of banking sector distress: (i) runs without failures, (ii) failures without runs, and (iii) failures involving runs. We find that spikes in the rate of runs without failure lead to modest declines in deposits and loans at both the city and state level. In contrast, failures without runs lead to more severe deposit and credit contractions. The most severe episodes involve spikes in banks subject to runs and failure, which are slightly more severe than episodes of failures without runs.

Our findings have two broad implications. First, while runs can occur in both weak and strong banks, poor fundamentals are necessary for runs to result in bank failures. Second, failures, and their corresponding weak fundamentals, are important for banking sector distress to translate into substantial deposit and credit contractions. Pure liquidity events, in which depositors run due to fear or confusion but bank fundamentals are sound, are not associated with severe economic outcomes at the local level.

Related Literature Our paper relates to a rich empirical literature on bank runs, bank failures, and financial crises (see, e.g., Sufi and Taylor (2021) and Frydman and Xu (2023) for overviews).

The main contribution of our paper is to provide insights from a novel comprehensive database that covers more than 4,000 bank runs in the historical U.S. banking system. This novel data allows us to provide systematic evidence on which banks become subject to bank runs and which banks fail in runs. Hence, our study relates to micro-level studies of bank runs. Existing evidence suggests that deposit growth is lower in relatively weaker banks (see, e.g. Chen et al., 2024) and especially when solvency concerns are salient

during crisis episodes (Schumacher, 2000). Jiang et al. (2023), Metrick (2024), and Cipriani et al. (2024) provide evidence that the banks most exposed to interest rate risk were those most affected by the banking stress in March 2023. Furthermore, previous work has shown that banks are able to withstand runs. For instance, banks can survive runs when they have strong ties to their depositors (Iyer and Puri, 2012). Runs by relatively less well-informed depositors are also less likely to result in failure (see, e.g. Grada and White, 2003; Saunders and Wilson, 1996; Calomiris and Mason, 1997; Blickle et al., 2024). Moreover, existing work suggests that interbank and wholesale markets may be crucial for how runs play out (Afonso et al., 2011; Perignon et al., 2018; Mitchener and Richardson, 2019).

Our paper also relates to studies of banking panics using aggregate or regional data. Gorton (1988), Calomiris and Gorton (1991), Alston et al. (1994), Wicker (1996), and Wicker (2006) present either time-series or regional evidence suggesting that U.S. banking panics from the National Banking Era through the Great Depression were largely predictable responses to fundamental shocks that altered depositors' perceptions of bank solvency. Baron et al. (2021) argue that widespread panic runs are not a necessary feature of banking crises, showing that panics are typically preceded by declines in bank equity prices that reflect the recognition of underlying losses. Greenwood et al. (2022) show that banking crises are predictable using credit growth and elevated asset prices. Jordà et al. (2020) find that while higher bank capitalization does not reduce the likelihood of banking crises, it is associated with stronger recoveries once crises occur. Jamilov et al. (2024) identify systemic bank runs with narrative evidence and observed deposit outflows and find that such runs occur infrequently, but when they do, they are associated with large, persistent output losses.

Our paper also relates to a rich literature on understanding bank failures. White (1984) shows that banks that failed during the 1930 banking crisis were less well capitalized than surviving banks, tended to have more illiquid assets, and relied more on wholesale funding. Calomiris and Mason (2003) document that most banks that failed throughout the Great Depression showed weaknesses in their balance sheets and argue that banking panics primarily accelerated the timing of failures among already weak banks rather than causing widespread collapse of otherwise solvent institutions. Correia et al. (2025) generalize the insight that weak fundamentals are a necessary condition for bank failures beyond the Great Depression and argue that failed banks were usually fundamentally insolvent based on recovery rates in failure. Our paper makes a distinct contribution to this literature by expanding the scope of bank distress to systematically include episodes beyond bank failures. We provide the novel insight that runs can occur in strong banks,

but they typically only result in failure for weak banks.

Finally, our paper contributes to the literature that shows that financial disruptions can have persistent consequences for the real economy by linking the consequences of both bank failures and bank runs without failures to real economic outcomes at the bank and local level. Bernanke (1983) emphasizes the role of credit market impairments in deepening the Great Depression. Chodorow-Reich (2014) provides micro-level evidence that credit supply shocks during the 2008–09 financial crisis led to substantial employment losses among firms dependent on weak lenders. Similarly, Frydman et al. (2015) document that runs on trust companies during the Panic of 1907 curtailed investment and dividend payments by connected firms, illustrating how financial distress transmits to the real economy even outside traditional banks.

2 Data

2.1 Novel Bank Distress Events Database

We construct a novel and comprehensive dataset of bank distress events—bank runs, suspensions, reopenings, and failures—recorded in newspapers for all U.S. banks between 1800 and 1963. Based on our data of distress events, we then identify bank-specific distress episodes in which the same bank is subject to one or more distress events within the same time period.

Concepts and Definitions The goal of our dataset is to identify "bank distress episodes" discussed in newspaper accounts at the bank-level. We define a bank distress episode as an episode with narrative discussion of a (i) bank run, (ii) suspension, and/or (iii) failure. Our conceptual definition of a bank run is a severe and sudden episode in which depositors or other creditors demand that the demandable liabilities of a given bank be converted into cash or into the liabilities of another bank. Our definition of a suspension is both a temporary closure of a bank (i.e., it fails to open its doors), as well as cases of partial suspension of convertibility. The latter case includes episodes when a bank suspends deposit withdrawals above a certain amount or suspends withdrawal of less liquid deposits, such as time deposits. In the Antebellum era, it also includes suspension of the conversion of state bank notes into specie. We define failures as suspensions that become permanent. This includes receiverships for national banks and some state banks, and assignments for private and other banks. We exclude orderly voluntary liquidations from failures. For our analysis that focuses on national banks, we define failure as national

bank receivership.

Sources We rely on several databases of historical newspapers. Our main source is the *Chronicling America* newspaper database (Library of Congress, 2025), a large-scale database of publicly available historical newspaper scans maintained by the U.S. National Digital Newspaper Program. To conduct our analysis at the article level, we draw on the *American Stories* dataset from (Dell et al., 2023) to separate pages into articles.[1] Because copyright limitations restrict the number of articles available in the *Chronicling America* database after the mid-1920s, we supplement the *Chronicling America* data with Newspapers.com and NewspaperArchive.com, two major commercial newspaper databases for the 1925-1934 period.[2] Figure C.2 shows the number of articles used in our final analysis across time and source.

Methodology We produce our dataset of bank distress events in two stages. The procedure is summarized in Figure 1. In the first stage (panel a), we process scanned newspaper images and obtain an intermediate dataset of articles related to bank-distress events. This stage has four components. In the first component, illustrated in Figure C.3, we perform a layout analysis of each page, segment pages into articles, and obtain each article's text through inexpensive but relatively imprecise OCR techniques. Next, we search each article with keywords and regular expressions (see Table C.1), and create a tentative list of articles related to bank distress. Third, we filter out obvious false positives with an off-the-shelf inexpensive LLM.[3] At this point, we have reduced the total number of newspaper articles by 99.8 percent (from 372 million to 679 thousand), so we are able to apply a more precise analysis. In the fourth and last step, we apply state-of-the-art OCR to obtain high-quality article text, and employ a more sophisticated LLM to i) determine if the article is really about bank distress, and ii) extract structured information from each article, including every date, event, and bank discussed. This results in an intermediate dataset of 242 thousand articles discussing 389 thousand bank-distress events (see Figure C.5 for some examples).

[1] *Chronicling America* provides scanned newspaper images together with metadata for each newspaper issue, as well as text obtained by applying reduced-quality optical character recognition (OCR) techniques. However, its key limitation for our purposes is that it provides content only at the page level and not at the article level. Moreover, the low quality of the text makes it challenging to apply textual analysis or even keyword matching methods. To address this, we use the *American Stories* dataset (Dell et al., 2023). This dataset provides, for most of the scanned pages in *Chronicling America*, layout information indicating the coordinates of each article, as well as text with an OCR quality good enough for keyword matching.

[2] The number of articles drops from 7.3 million articles in 1922 to 2.6 million articles in 1923 and only 1.3 million articles by 1930 (see Figure C.1).

[3] See Listing C.1 for the LLM prompt used and Figure C.4 for some examples of articles filtered out.

At this stage, the dataset has the drawback of being at the article-bank-event level rather than at the bank-event level. Thus, a given bank run might be discussed multiple times throughout many articles. For instance, the failure of the Knickerbocker Trust Company in 1907 was discussed in over 1,000 articles. Further, a single article might not be enough to understand the nature of a bank distress episode, as it might assumes some degree of knowledge from earlier articles.

To address this, in the second stage summarized by Figure 1 panel (b), we transform the intermediate article-bank-event dataset into our final dataset at the bank-episode level. This is done in roughly two steps. First, we validate and standardize state, city, and bank names. This allows us to group all articles for a given bank and to combine this data against datasets with bank balance sheet information, receivership records, and city- or state-level economic indicators. Appendix C.2 discusses how we standardize state and city names. This step is relatively straightforward and correctly matches more than 99 percent of non-missing records against existing city-level datasets. However, standardizing bank names is considerably more challenging, as there is no comprehensive list of bank names across bank types (national, state, private) or historical periods (Antebellum, National Banking Era, Federal Reserve). To overcome this challenge, we collect an exhaustive list of existing bank-level datasets and write a Python package that allows for name matching that is robust to typos and variations on how bank names are written.[4] This allows us to match 65% of all bank names between 1800 and 1963, and up to 88% if we focus only on national banks for 1863-1935.[5]

In the final step, for each bank we group all the events that take place within a period of time of up to 365 days. These groups of events capture what we call "bank distress episodes," which we analyze by feeding the corresponding newspaper articles to more advanced LLMs. We ask the LLMs to jointly analyze all newspaper articles that describe a given bank distress episode, reclassify all the details of this episode, including event types and dates, and finally classify the type of the overall episode depending on its internal dynamics. To minimize classification errors, we combine queries to independent LLMs, and apply a final manual review.[6]

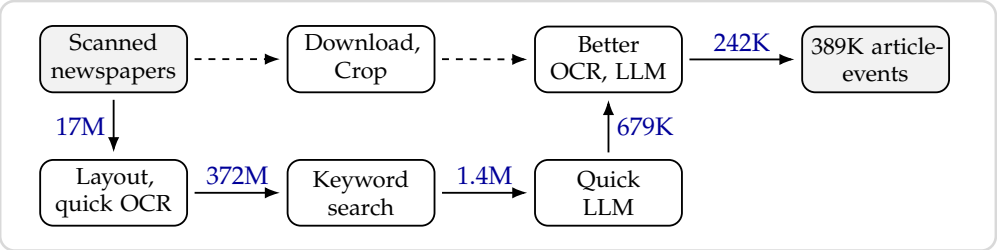
Episode Types Our bank distress episodes can be interpreted as a self-consistent list of events that affected a specific bank. We classify bank distress episodes into the following

[4]See Appendix C.3 for additional details.

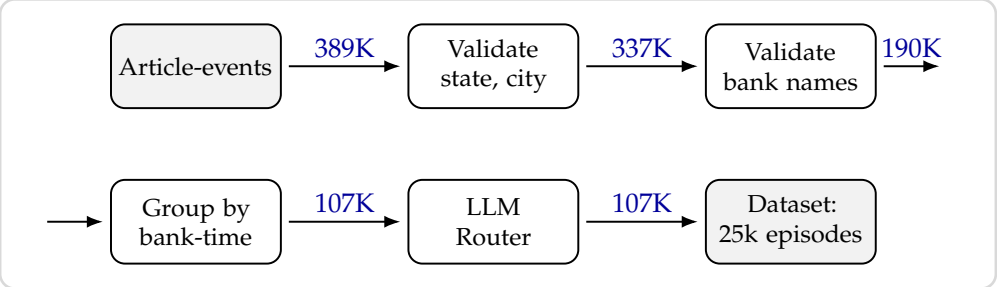
[5]We do not truly know if a bank is a national bank unless we can match it, so as a workaround we proxy for national banks with banks that contain the string "nat", which captures "National," "Natl.", etc.

[6]Due to cost and current limitations in LLMs, we only include up to ten articles for each bank episode queried.

Figure 1: *Methodology for Constructing the Bank Distress Episodes Database*



(a) *Identify events about bank distress*



(b) *Combine article-level events into bank distress episodes*

Notes: This figure summarizes the steps involved in constructing our main bank distress episodes dataset. The numbers in blue indicate how many newspaper articles—or page scans, for the first arrow—carry forward from one step to the next. Panel (a) describes how we construct our intermediate dataset, where every row corresponds to a bank-level event from a given newspaper article. To do so, we first extract newspaper articles from each page, then we identify the articles related to bank-distress events, and lastly we obtain structured information from each article about specific events involving banks, such as runs, suspensions, failures, and reopenings. We obtain an intermediate dataset composed of 242 thousand articles discussing 389 thousand events. Panel (b) then shows how this intermediate dataset is transformed into our final dataset at the bank-episode level. This is done by first standardizing state, city, and bank names. We then group the articles by bank and time into episodes and query LLMs for detailed episode-level information. We obtain a final dataset of 25 thousand episodes, with each episode containing on average 2.2 specific events. The dataset covers the years 1800-1967. Our main analysis focuses on 1863-1934 period, which covers the National Banking Era and the pre-deposit insurance Federal Reserve Era.

categories based on their internal dynamics:

(I) *Run only.* A bank run takes place, but the bank remains open throughout the bank run and the bank run stops on its own. The bank does not suspend or fail.

(II) *Run-suspension-reopening.* A bank run takes place. As a consequence of the bank run, the bank suspends (either fully by suspending all payments or partially by invoking the 30/60/90 day rule). However, the bank eventually reopens and does not fail.

(III) *Run-suspension-failure.* A bank run takes place. The bank suspends all payments. The bank remains closed permanently and has either a receiver assigned or is taken

over by another bank.

(IV) *Suspension-reopening.* A bank suspends. The bank is able to reopen successfully and continues to operate its business.

(V) *Suspension-failure.* A bank suspends. The bank remains closed permanently and has either a receiver assigned or is taken over by another bank.

We also consider two other types of events in which a suspension precedes narrative accounts of a run. These turn out to be empirically less relevant:

(VI) *Suspension-run-failure.* A bank suspends. As a consequence of the suspension, depositors run and/or are excited (i.e., they gather outside the bank) in an ill-fated attempt to regain access to their funds. The bank remains closed permanently and has either a receiver assigned or is taken over by another bank.

(VII) *Suspension-run-reopening.* A bank suspends. As a consequence of the suspension, depositors run and/or are excited (i.e., they gather outside the bank) in an ill-fated attempt to regain access to their funds. The bank is able to reopen successfully and continues to operate its business.

For much of the analysis, we group the events into whether or not they involve a run. Episodes involving a run are (I), (II), (III), (VI), and (VII). Episodes involving bank failure are (III), (V), and (VI).[7] With this, we can consider episodes with runs but no failure, failure but no run, and failure and run.

We briefly note two measurement issues that are important to keep in mind. First, our database records binary information on whether a run occurred across various types of episodes, but the severity of what constitutes a run can differ, as we will show. Second, newspapers may not always report runs. This concern applies especially to smaller banks. As with any narrative classification, there is always a concern that an event is not discussed in the narrative accounts under consideration. There can be episodes of "quiet" distress. Nevertheless, we do find that newspapers contain a massive amount of valuable information when validating our measure against existing narrative chronologies of banking crises or existing information on bank failures for national banks, as we discuss further below.

[7]Moreover, for our analysis using national banks, we rely on information on whether a bank failed directly from the OCC Annual Report to Congress digitized in Correia et al. (2025).

2.2 Additional Data Sources

We combine the list of bank distress episodes with bank financial data for national banks. We use balance sheets of national banks from 1863-1941 from Correia et al. (2025), based on national bank call reports submitted in the OCC's Annual Report to Congress.[8] These data contain detailed balance sheet line items, including total assets, loans, securities, deposits, equity capital, and noncore (non-deposit and non-equity) funding.

For national banks, we use the precise information on closures of national banks (receivership, mergers, assignment, and voluntary liquidations) from van Belkum (1968), Huntoon (2023), and Correia et al. (2025). 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 explicitly does not include temporary suspensions. To measure the extent of the deposit outflow in a bank failure, we further use deposits at suspension based on data on OCC receiverships digitized by Correia et al. (2025).

To proxy for local real economic activity, we create a dataset of quarterly commercial failures covering 1886-1935 by digitizing various issues of *Bradstreet's*. Finally, we use information on the banking crisis years and the month of banking panics from Baron et al. (2021), as well as information on regional banking panics from Jalil (2015).

3 Bank Distress Episodes in the US, 1863-1934

This section provides an initial look at the incidence of bank distress episodes in the US from 1863 to 1934. In the process, we validate the quality of our newly constructed database.

3.1 Descriptive Statistics on Bank Distress Episodes

Table 1 shows the raw counts and shares of different episode types. Figure 2 shows a Venn diagram of episodes with a run, suspension, and/or failure. Recall that each observation represents an episode of bank distress for a particular bank, with the same bank possibly being subject to distress at different points in time over the sample period. Focusing on the period 1863-1934, our dataset contains 4,334 episodes involving a run,

[8]The data in Correia et al. (2025) build on the data in Carlson et al. (2022) and are digitized using the OCR techniques developed in Correia and Luck (2023).

Table 1: ***Bank Distress Episodes in Newspapers, 1863-1934***

Era	Runs/Suspension without Failure				Failure		
	All	Run Only	Run+Suspension	Suspension	All	No Run	Run
All	4437	1569	736	2132	12913	11004	1909
No crisis	1880	873	275	732	8407	7383	1024
Banking crisis	2557	696	461	1400	4546	3661	885
1863-1913 (NB Era)	2294	1099	379	816	5643	4789	854
1914-1918 (Early Fed)	567	214	114	239	2891	2544	347
1929-March 6, 1933	814	224	221	369	3167	2502	665
After March 6, 1933	762	32	22	708	1212	1169	43

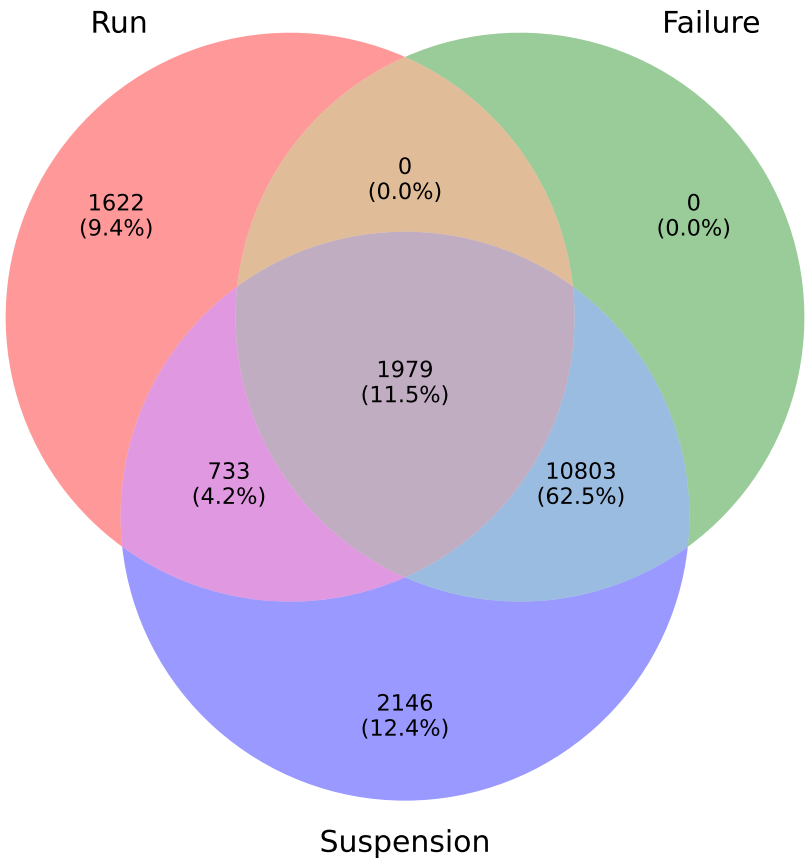
Notes: This table reports the counts of all bank distress episodes that we identify in newspapers from 1863 to 1934. The sample covers bank distress episodes for all bank types, including state banks, trust and private banks. We distinguish between distress episodes that, according to the newspaper, resulted in failure and those that involved a bank run and/or a bank suspension but no bank failure. We further split the sample by different eras (National Banking Era, Early Federal Reserve, and Great Depression before and after the 1933 banking holiday) and whether a year involved a major banking crisis or not as identified in Baron et al. (2021).

15,661 episodes involving a suspension, and 12,782 episodes involving a failure. Thus, the majority of distress episodes involve a bank failure. Note that a bank must suspend before it fails. Hence, by definition, there are no failures without suspensions. At the same time, there are many episodes involving runs or temporary suspensions that do not result in failure. For instance, we find 2355 bank runs that do not involve failure. There are also more than 2000 suspensions without runs that do not result in failure.[9]

The fact that we observe many runs *without* failure is somewhat surprising and constitutes the first insight of our new data. In basic theories of bank runs that combine strategic complementarities and large fire sale discounts (Diamond and Dybvig, 1983; Goldstein and Pauzner, 2005), runs, when they occur, result in failure. There exists no equilibrium with a run without failure. However, in a non-trivial share of cases, when runs occur, banks do not fail. The occurrence of runs or suspensions without failure is in line with asymmetric information theories of runs, where depositors run on a bank when a public signal such as a long line at the bank leads them to infer the bank is insolvent, sometimes incorrectly. It is also consistent with theories where runs are a monitoring device. In these theories, a run does not lead to failure if the bank is revealed to be solvent

[9]Note that we "only" identify around 700 suspensions after the Banking Holiday in 1933 when all banks suspended (see, e.g., Jaremski et al., 2023). This is explained by the fact that newspapers may not have seen a need to report individual bank suspensions right around the time the entire banking system suspended.

Figure 2: *Bank Run, Suspension, and Failure Episodes*



Notes: The sample is all bank distress episodes involving combinations of run, suspension, and or bank failure over the period 1863-1934. By definition, failure requires suspension, so there are no observations with failure without suspension.

after an examination triggered by the run (Gorton, 1985). Runs without failure are also potentially consistent with panic runs arising from non-rational behavior by depositors. We explore the determinants of runs that result in failure and those that do not in detail in the next section.

Table 2 shows the unconditional probability of bank distress episodes for our 1863-1934 panel of national banks merged with bank distress episodes. To calculate probabilities of bank distress, we focus on national banks, where we have a precise measure of the total number of banks for the entire sample. Moreover, for national banks, we have clear records that determine whether a bank failed as the OCC recorded whenever a receiver was appointed.[10] Table 2 shows that a national bank's unconditional probability of failing

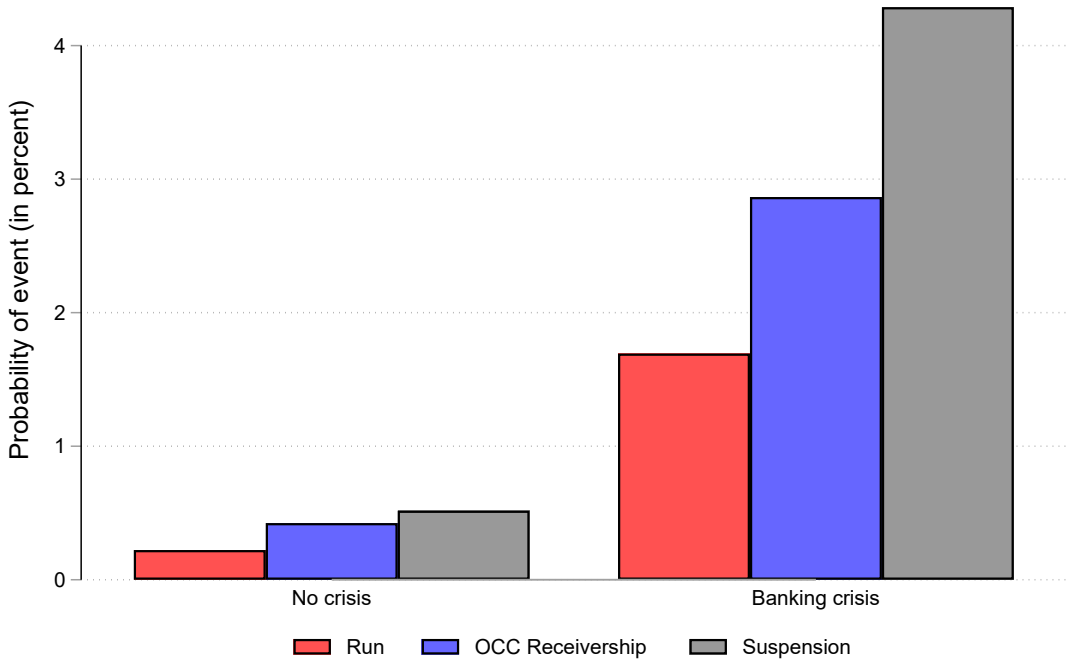
[10]There is no census on the universe of non-national banks. Moreover, there is no systematic information

between 1864 and 1934 is 0.7%. However, over the same time, national banks also face an unconditional 0.5% chance of being subject to a bank run or to temporarily suspend business without failing. Hence, bank failures are only slightly more likely to happen than bank runs or suspensions without failure.

3.2 Bank Distress Episodes and Narrative Banking Crises

We next establish that bank distress episodes of all kinds are more likely during major banking crises. Figure 3 plots the probability of bank distress episodes for national banks from 1863-1934 during and outside of banking crisis years. Crisis years are based on the narrative chronology of Baron et al. (2021). We consider runs, suspensions, and failures. Figure A.1 in the appendix shows the breakdown by more detailed episode types.

Figure 3: ***Probability of Bank Distress Episodes for National Banks During and Outside of Banking Crises***



Notes: The figure plots the probability of bank runs (with and without bank failure), bank failures (defined as OCC receiverships) and suspensions (bank failure but also bank runs and suspensions that do not result in failure) during and outside of years identified as banking crises in Baron et al. (2021). The sample is based on all national banks from 1863-1934.

The figure shows that bank runs, suspensions, and failures are all much more likely

on failures of state banks or trusts. Therefore, much of our analysis relies on the merged sample of national banks.

during banking crisis years. For example, the probability of a bank distress event without failure increases by a factor of 8 during banking crisis years. The probability of a bank failure increases by a factor of more than 6 in banking crisis years. Further, Table 2 shows a more detailed breakdown of the probability of various distress episodes for all years and separating by years with and without a banking crisis. For instance, bank runs that trigger a suspension but do not result in failure become 14 times more likely. Moreover, not surprisingly, bank runs and suspensions that do not result in failure are also much more likely during banking crises. Taken together, our newly constructed data confirm that banking panics of the pre-deposit insurance era featured many bank distress episodes, but also highlight that these often times included runs/suspensions that did not result in failure.

Table 2: ***Probability of Bank Distress Episodes for National Banks, 1863-1934***

Sample	Runs/Suspension without failure				Failure	
	All	Run Only	Run+Suspension	Suspension	All	With Run
All	.449	.17	.0609	.22	.72	.121
No crisis	.204	.0995	.0231	.000817	.424	.000725
Banking crisis	2.21	.679	.332	.0121	2.87	.00478
1863-1913 (NB Era)	.415	.187	.0663	.164	.302	.091
1914-1918 (Early Fed)	.133	.0831	.0169	.0326	.614	.075
1929-March 6, 1933	.715	.358	.153	.203	3.9	.722
After March 6, 1933	3.37	.0775	.0969	3.2	6.15	.107

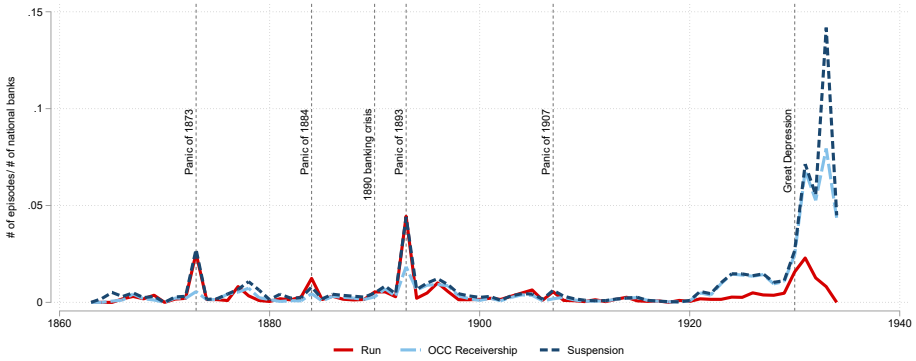
Notes: This table reports the number of the type of distress episode indicated in the table header divided by the number of national banks in the same year, averaged across all years for the sample indicated in the table header. A bank failure is defined as an OCC receivership. The number of national banks and OCC receiverships per year comes from Correia et al. (2025). The first column reports the probability of different types of distress episodes for the sample from 1863 through 1934. We further split the sample by different eras (National Banking Era, Early Federal Reserve, and Great Depression before and after the 1933 banking holiday) and whether a year involved a major banking crisis or not, as identified in Baron et al. (2021). Banks that suspend but do not fail reopen their business.

Figure 4 plots the number of bank distress episodes as a fraction of the total number of banks over time at the annual level.[11] Panel (a) plots the fraction of national banks subject to a distress episode involving a run, suspension, or failure. Runs and suspensions spike during all major banking crisis years. Failures spike during some of the crisis years,

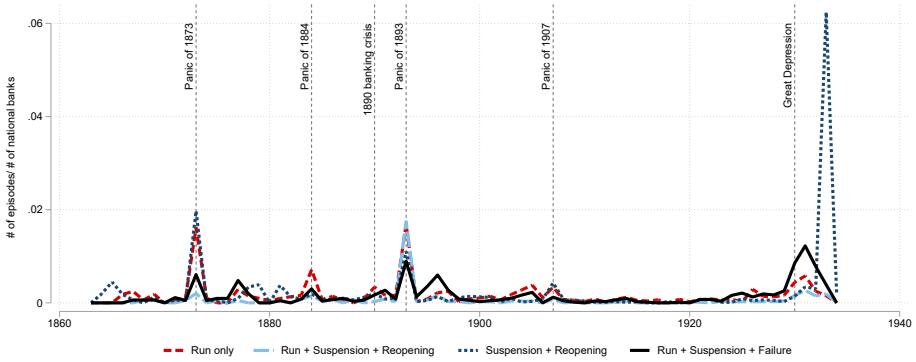
[11]Raw counts of distress episodes for all banks are reported in Appendix Figure A.2.

Figure 4: ***Bank Distress Episodes of National Banks in Newspapers from 1863-1935***

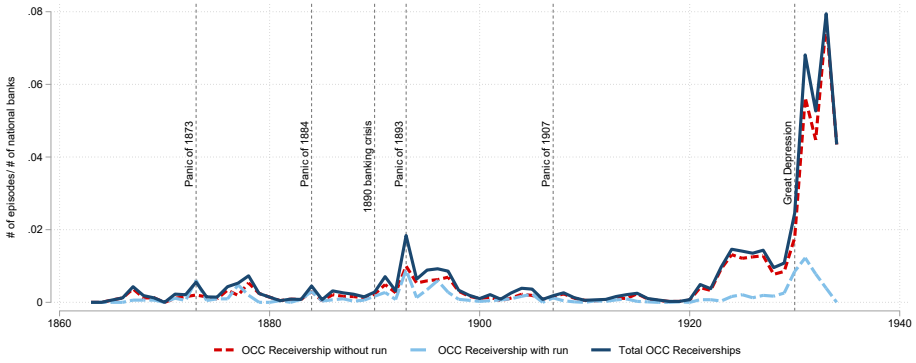
(a) *Runs, Suspensions, and Failures*



(b) *Distress Episodes Involving Runs*



(c) *Distress Episodes Involving Failure*



Notes: This figure plots the ratio of the number of national banks subject to a distress episode over the number of events by the total number of national banks in each year as reported in Correia et al. (2025). In panel (a), we report episodes involving runs, episodes involving failure, and episodes involving suspension. In panel (b), we report distress episodes that involve bank runs, distinguishing between episodes that do not result in suspension, result in suspension but not failure, and those that result in failure. In panel (c), we show the number of OCC receiverships that are associated with runs in newspapers and those that are not associated with runs.

such as 1893 and the Great Depression. However, other crises, such as 1873 or 1884, saw

limited national bank failures compared to runs, as noted in prior work (e.g., Calomiris and Gorton, 1991).

Panel (b) in Figure 4 zooms in on episodes that involve runs. We distinguish between bank runs that do not result in a suspension, runs or suspensions that are followed by a reopening of the bank, and bank runs that ultimately resulted in failure. Episodes that featured bank runs and suspensions that do not result in failure are most common during major banking crises. The Panic of 1893 featured a particularly large number of suspensions with reopening, as noted by previous work (e.g., Carlson, 2005). The data also picks up the large wave of suspensions and reopenings during the banking holiday of 1933.

Panel (c) in Figure 4 plots bank failures with and without runs. Most failures do not involve narrative discussions of runs, so the "OCC receiverships without run" line usually lies above the "OCC receiverships with run" line. Failures with runs spiked during the Panic of 1893 and the Great Depression. Failures without runs were elevated during the 1890s and 1920s agricultural downturn.

Figure A.3 plots the rate of bank runs and bank failures at the monthly frequency. In vertical lines, we plot the monthly start date of banking panics according to (Baron et al., 2021). Bank run spikes line up remarkably well with the month of banking panics from narrative accounts. Newspapers also pick up several additional borderline cases of banking panics, such as 1896.

We next show in a regression framework that bank distress events are substantially more likely in years and U.S. states that have been classified as having a banking crisis/panic in previous work. Table 3 examines whether our list of bank distress events lines up with the narrative banking crisis dates from Jalil (2015) and Baron et al. (2021). Jalil (2015) provides information on state-level banking panics,[12] while Baron et al. (2021) provide years of the onset of banking crises. With this narrative information, we estimate the following regression at the state-month level:

$$\begin{aligned} \text{Bank Distress Event}_{st} = \beta_0 + \beta_1 \times \text{BVX Crisis}_t \\ + \beta_2 \times \text{Non Major Banking Panic}_{st} + \epsilon_{st}, \end{aligned} \tag{1}$$

where BVX Crisis_t is a dummy that takes a value of one in years defined as banking crises by Baron et al. (2021) and $\text{Non Major Banking Panic}_{st}$ is a dummy that takes the value one if a state is subject to a banking panics according to Jalil (2015) in a given month.

On average, we find that there are 0.4 bank distress events per state per month. During

[12] Jalil (2015) also reports city-level panics, which we aggregate to the state level.

years with a banking crisis, the number of events in a state increases by 1 on average. During phases of non-major regional banking crises, the number increases by 0.5. This is driven by an increase in runs/suspensions and by an increase in failures. Further, we include dummies for individual regional crises identified by Jalil (2015) in the regression. Individual crises see considerable increases in the number of events. For instance, the number of distress events increases by a striking 36 during the Florida "Fruit Fly Panic" in July 1929 (Carlson et al., 2011). Overall, our database of bank distress events correlates strongly with existing narrative chronologies of banking crises in U.S. history.

Table 3: ***Narrative Banking Crisis Classifications and Bank Distress Events***

Dependent variable	Total Events			Run/Suspension without Failure			Failure	
				All	Run Only	Sus	Fail	Fail with Run
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
BVX Crisis	2.03***	2.04***	2.05***	0.85***	0.14***	0.72***	1.13***	0.27***
	(0.26)	(0.26)	(0.26)	(0.082)	(0.026)	(0.077)	(0.21)	(0.038)
BVX Panic Month	3.08*	2.80*	2.71**	2.31**	1.07**	1.25**	0.21	0.48**
	(1.57)	(1.46)	(1.33)	(0.96)	(0.45)	(0.58)	(0.38)	(0.20)
Nonmajor Banking Panic (Jalil)		10.4***						
		(1.88)						
May 1884 (NYC, PA, NJ)			17.8*	10.9	10.0	0.90	6.18**	2.11*
			(10.5)	(7.84)	(6.11)	(1.78)	(2.76)	(1.23)
Nov. 1890 (New York City, NY)			1.17*	0.24	1.21***	-0.98***	1.12***	-0.15
			(0.70)	(0.51)	(0.26)	(0.29)	(0.24)	(0.10)
Dec. 1896 (IL, MN, WI)			14.2**	6.08**	4.22**	1.86**	8.19***	3.53***
			(5.64)	(2.63)	(1.80)	(0.83)	(3.06)	(1.20)
Dec. 1899 (Boston, MA; NYC, NY)			7.57***	1.75***	0.38	1.36***	5.85***	0.36
			(1.45)	(0.020)	(0.37)	(0.36)	(1.44)	(0.36)
June–July 1901 (NY: Buffalo; NYC)			6.57***	0.75***	-0.12***	0.86***	5.85***	-0.14***
			(0.058)	(0.020)	(0.017)	(0.0085)	(0.055)	(0.0095)
Oct. 1903 (PA, MD)			0.57***	1.75***	1.88***	-0.14***	-1.15***	-0.14***
			(0.058)	(0.020)	(0.017)	(0.0085)	(0.055)	(0.0095)
Dec. 1905 (Chicago, IL)			2.57***	0.25***	0.38***	-0.14***	2.35***	0.86***
			(0.058)	(0.020)	(0.017)	(0.0085)	(0.055)	(0.0095)
Jan. 1908 (NYC)			7.57***	1.75***	-0.12***	1.86***	5.85***	3.86***
			(0.058)	(0.020)	(0.017)	(0.0085)	(0.055)	(0.0095)
Aug.–Sept. 1920 (Boston)			3.57***	1.75***	0.88***	0.86***	0.85***	1.86***
			(0.058)	(0.020)	(0.017)	(0.0085)	(0.055)	(0.0095)
Nov. 1920–Feb. 1921 (ND)			11.6***	3.75***	-0.12***	3.86***	7.85***	0.86***
			(0.058)	(0.020)	(0.017)	(0.0085)	(0.055)	(0.0095)
July 1926 (FL, GA)			3.57***	0.75***	-0.12***	0.86***	1.85***	0.86***
			(0.058)	(0.020)	(0.017)	(0.0085)	(0.055)	(0.0095)
March 1927 (FL)			20.6***	6.75***	1.88***	4.86***	9.85***	5.86***
			(0.058)	(0.020)	(0.017)	(0.0085)	(0.055)	(0.0095)
July–Aug. 1929 (FL)			35.6***	7.75***	2.88***	4.86***	24.9***	11.9***
			(0.058)	(0.020)	(0.017)	(0.0085)	(0.055)	(0.0095)
Observations	9159	9159	9159	9159	9159	9159	9159	9159
R^2	0.074	0.092	0.10	0.065	0.094	0.041	0.084	0.088
Mean dep. var.	1.93	1.93	1.93	0.48	0.17	0.31	1.41	0.21

Notes: This table shows results from estimating Equation (1). Sample of events 1865 through 1934. Standard errors clustered at the state level. *,**, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

3.3 Additional Data Quality Checks

We perform several additional basic data quality checks for our bank distress episodes dataset. For these checks, we focus on the sample of national banks, as we know the true incidence of failures from the OCC's records of receivership for this sample. Moreover, we also observe the actual deposit outflows for banks that end up failing between the last call report and the date of failure.

First, we correlate the true failure rate for national banks with the failure rate according to our classification from newspapers. We construct an alternative failure rate from our bank distress episodes database by dividing the number of episodes with a national bank failure in newspapers by the total number of national banks. Figure A.5a shows that the overall fit is good, but not perfect, as one might expect. Our alternative failure rate based on newspapers has too many failures in the 1890s, but captures too few failures in the 1920s and 1930s. In the same spirit, Figure A.5b compares the number of national bank failures mentioned in newspapers and the number of OCC receiverships at the monthly level. The slope of the relation is almost unity, the intercept is almost zero, and the R^2 is 54%. One month that does not line up closely is March 1933 (bottom right corner of the plot). The reason is that many banks that suspended in the March 1933 Bank Holiday only had a receiver formally appointed later in 1933 or 1934.

Second, Figure A.5e plots the probability of a bank distress event reported in newspapers as well as the actual annual rate of bank failures by bank size, measured using total assets. It reveals that our bank distress events database from newspaper accounts is more likely to report events for larger banks. Given that distress events for larger banks are more newsworthy, we are more likely to under-report events for smaller banks. This is an important qualification to keep in mind.

Third, Figure A.5d plots the distribution of actual deposit outflows in national bank failures for failures with and without a bank run according to our bank distress episodes database. Deposit outflows are measured as the growth in deposits from the last call report before suspension to the time of suspension. The figure shows that failures with narrative evidence of a run in newspapers have larger deposit outflows before failure. On average, failures with narrative evidence of a run exhibit a roughly 10 pp larger deposit outflow before failure. While our bank distress events database may not capture all runs—either because they are not mentioned in newspapers in our corpus or because our methodology misses these runs—this provides evidence that narrative accounts of runs in newspapers capture many failures with large deposit outflows.

4 Bank Runs and Failures

What are the characteristics of banks subject to runs? Which runs lead to bank failure? Can a run lead to the failure of a healthy bank? Or do runs only lead to failures for fundamentally weak banks?

This section shows that runs are more likely in banks with weak fundamentals, but even strong banks can be subject to runs. However, a run is much more likely to translate into failure for weak banks. Runs essentially never result in failure for banks with strong fundamentals. Moreover, failing banks display weak and deteriorating fundamentals, irrespective of whether they fail with or without a run.

4.1 Characteristics of Banks Subject to Runs and Failures

We first assess the likelihood of a bank run or bank failure across weak and strong banks, measured by bank-level fundamentals. The sample is all national banks from 1863 to 1934, as this analysis requires data on bank-level fundamentals. Our goal here is to describe the relationship between bank fundamentals and the likelihood of the various distress episodes. To do this, we estimate regressions of the following form:

$$\text{Bank Distress Episode}_{bt+1} = \beta_0 + X_{bt}\beta + \epsilon_{bt+1}, \tag{2}$$

where $\text{Bank Distress Episode}_{bt+1}$ is an indicator variable for whether bank b is subject to a bank distress episode within the next year. We focus on four types of distress episodes: bank runs, bank runs that do not result in failure, failures, and failure with a run.

On the right-hand side, we include a range of fundamental balance sheet metrics in X_{bt} to proxy for bank health and risk-taking. These measures have been shown to capture the risk of bank failures in prior work (e.g., White, 1983; Calomiris and Mason, 1997; Correia et al., 2025). First, we proxy for bank solvency with the surplus-to-equity ratio. Surplus profit captures past retained earnings and is thus a measure of past bank profitability and capitalization.

Second, we include a measure of noncore funding, defined as non-deposit and non-equity funding. This measure includes wholesale funding, such as bills payable and rediscounts. Noncore funding tends to be more expensive and risk-sensitive than deposit funding. Existing work shows that reliance on noncore funding was often a signal of banks suffering losses to their assets or deposit franchise value (e.g. White, 1984; Calomiris and Mason, 1997). We also interact the solvency and noncore funding measures, as banks with low solvency and high reliance on noncore funding might be especially likely to

experience future distress.

Third, we include the liquid assets ratio as a proxy of the riskiness of a bank's investment mix. Fourth, we include deposits-to-assets as a measure of leverage. Finally, we include recent asset growth. Troubled banks often contract shortly before failure, so recent asset growth contains information about the future likelihood of failure.

In addition to the estimated coefficients, we are interested in the extent to which observable fundamentals predict bank distress episodes. We therefore report the area under the receiver-operating characteristic curve (AUC). The receiver-operating characteristic (ROC) curve traces out the true-positive rate against the false-positive rate as we vary the classification threshold. The AUC is the integral under the ROC curve. An AUC of 1 indicates perfect classification performance, while an AUC of 0.5 indicates an uninformative predictor.

Table 4 presents the results from predicting bank runs or failures as a function of bank fundamentals. The table shows that banks with low solvency (proxied by surplus-to-equity) and a high reliance on noncore funding are more likely to be exposed to runs and to fail. The interaction between the solvency and noncore funding measures is also highly predictive of bank failures. Further, banks with high leverage (deposits/assets) and banks with low asset growth are more likely to fail.

Most importantly, comparing columns 1-2 and 3-4 in Table 4 reveals that bank failures are substantially more predictable than bank runs. The AUC in columns 1-2 shows that runs are only weakly predictable. The in-sample AUC of about 0.66 suggests a moderate degree of predictability for all runs. Run without failure in column 2 are even less predictable, with an AUC of 0.58. When conducting out-of-sample prediction, we find even lower AUCs, indicating essentially no predictability of runs without failures. The lower predictability is also consistent with the smaller and less statistically significant coefficient estimates. This is especially striking when considering runs without failure in column 2, where none of the estimates is statistically significant. This evidence suggests that runs that do not result in failure are less tightly linked to bank fundamentals, making these distress episodes less predictable.

In contrast to runs, bank failures are substantially predictable, as seen in columns 3-4. This confirms the evidence in Correia et al. (2025). The AUC for all failures is 0.86, indicating substantial predictability. Failures with narrative evidence of a run are nearly as predictable as all failures (column 4), with an AUC of 0.81. Thus, failures involving runs are also linked to weak observable bank fundamentals, in sharp contrast to runs without failures.

We next present a visualization of the relationship between bank fundamentals and

Table 4: *Predictability of Bank Runs and Failures Based on Fundamentals*

Dependent variable	Run in $t+1$	Run without failure in $t+1$	Failure in $t+1$	Failure with run in $t+1$
	(1)	(2)	(3)	(4)
Surplus/Equity	-0.37***	0.02	-1.75***	-0.37***
	(0.13)	(0.07)	(0.48)	(0.10)
Noncore funding	8.02***	0.19	70.95***	6.65***
	(2.17)	(0.55)	(16.66)	(1.60)
Surplus/Equity × Noncore funding	-6.27**	0.70	-95.81***	-5.27***
	(2.70)	(1.29)	(20.64)	(1.85)
Liquid Assets/Assets	-0.56**	-0.18	-0.47	-0.37***
	(0.26)	(0.17)	(0.46)	(0.12)
Deposits/Assets	0.57	-0.02	2.94***	0.53**
	(0.38)	(0.14)	(1.04)	(0.24)
Asset Growth (3 years)	-0.17	0.06	-2.14***	-0.22**
	(0.14)	(0.05)	(0.69)	(0.11)
N	283417	283417	283417	283417
Mean dep. var	.37	.18	.81	.18
AUC	0.667	0.573	0.868	0.781

Notes: This table presents estimates of Equation (2). Driscoll-Kraay standard errors in parentheses. *,**, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

the likelihood of a run or failure. We construct a simple bank-level measure of fundamentals, Fundamentals$_{bt}$, based on the regression in column (3) of Table 4. The idea is to summarize fundamentals that are predictive of failure into one number, akin to an Altman Z-score (Altman, 1968). To avoid look-ahead bias, we estimate the regression iteratively using data up to $t-1$ to obtain predicted failure probabilities for time t. Fundamentals$_{bt}$ is then defined as the negative of the predicted value from the regression that predicts failure in year $t+1$.

Figure 5 panel (a) shows the conditional probability of a distress episode over the next year across deciles of our proxy for fundamentals. Runs are more likely in banks with weak fundamentals. A bank in the lowest decile of fundamentals has a 100 basis point probability of being exposed to a run. The probability drops to about 20 basis points for strong banks. Thus, while much less likely, strong banks can be subject to runs.

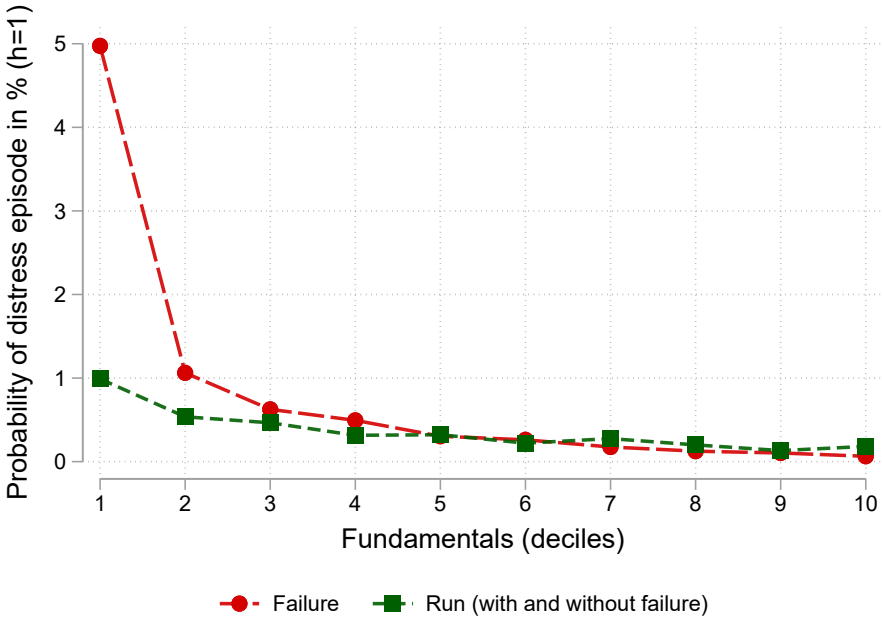
Figure 5 panel (a) also plots the relationship between fundamentals and the likelihood of bank failure. The relationship between fundamentals are failure is substantially stronger than for runs. Thus, failures are more predictable than runs. We note that this is not simply a mechanical consequence of how we construct the fundamentals measure. Table 4 showed that runs are systematically less predictable than failures.

4.2 Bank Runs and Failure across Weak and Strong Banks

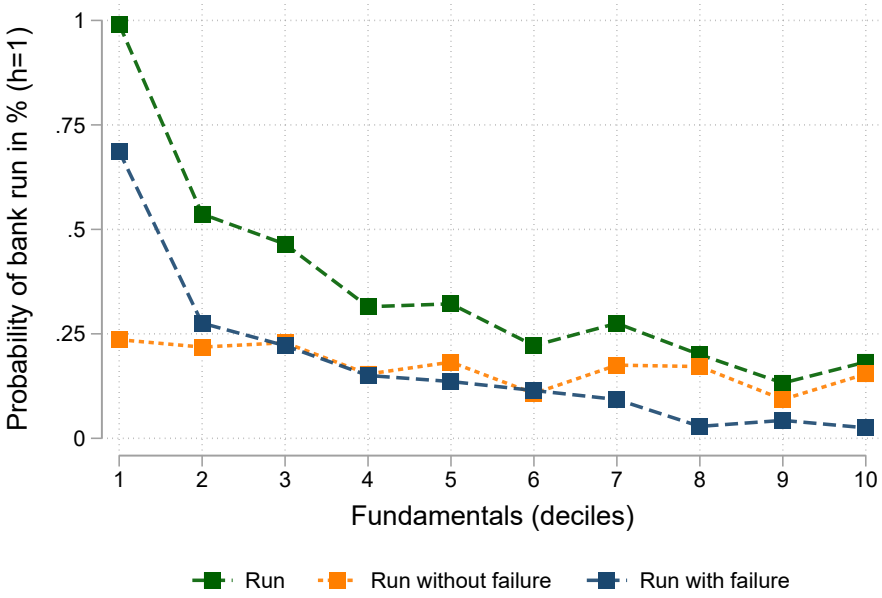
We next show that a bank is much more likely to fail when it is subject to a run. However, this is driven by banks with weak fundamentals. A run is much less likely to result in

Figure 5: ***Probability of Bank Run and Failure by Bank Fundamentals***

(a) *Bank runs and bank failures*



(b) *Runs with and without Failure*



Notes: Panel (a) plots the probability of a bank run (both runs that result in failure and those that do not result in failure) and bank failure (OCC receivership) against a proxy of bank fundamentals (see text for definition). Panel (b) splits runs into episodes with and without bank failure.

failure if a bank has *ex ante* strong fundamentals.

Panel (b) of Figure 5 plots the probability of runs with and without failure across the

distribution of bank fundamentals. Runs that do not result in failure are only weakly related to fundamentals (see the yellow line). These runs, though they are slightly more common in weak banks, are almost equally likely to happen in both weak and strong banks. On the other hand, runs with failure essentially only occur in banks with weak fundamentals (see the blue line). A bank that is in or above the 8th decile of the fundamentals distribution will essentially never fail when being subject to a run. Runs with failure are almost exclusively concentrated in banks in the lowest decile of fundamentals. Hence, even though strong banks can be subject to a bank run, for a run to be associated with failure, a bank must have weak fundamentals.

We formally study the importance of fundamentals for whether a bank can withstand a run by estimating the following model

$$\begin{aligned} \text{Failure}_{bt} = \beta_0 + \beta_1 \text{Run}_{bt} + \beta_2 \text{Fundamentals}_{bt-1} \\ + \beta_3 \text{Run}_{bt} \times \text{Fundamentals}_{bt-1} + \epsilon_{bt}, \end{aligned} \tag{3}$$

where Failure_{bt} is an indicator for whether bank b fails in year t, Run_{bt} is an indicator for whether the bank is exposed to a run in year t, and $\text{Fundamentals}_{bt-1}$ is our proxy for bank health measure in year $t-1$, defined above. We also present regressions where we interact the run indicator with the various proxies of bank fundamentals separately. This specification asks whether a run is associated with an increased likelihood of failure over the next year and how this varies across banks with weak and strong fundamentals.

Before proceeding, we stress that the regression in Equation (3) should not be interpreted causally. For example, a run may occur because there is public information about losses and fraud that are not measured in bank financial statements. Therefore, even for a bank with strong observables based on our proxy, Fundamentals_{bt}, a run may not be the root cause of failure if these observables do not capture large unrealized losses or fraud. Our goal here is to understand the relation between runs and failures across observably weak and strong banks.

Table 5 presents the results from estimating Equation (3) for the sample of national banks from 1863 to 1934. Column 1 shows that 39% of bank runs are associated with a bank failure. Thus, runs often result in failure. At the same time, most runs are not followed by failure.

Column 2 in Table 5 shows that banks with strong fundamentals have a significantly lower probability of failure. Moreover, strong fundamentals significantly cut the probability that a run is associated with a bank failure. In column 3, we interact the run indicator with an indicator for whether a bank's fundamentals, $\text{Fundamentals}_{bt-1}$, is above the

Table 5: ***Bank Runs and Failures across Banks with Weak and Strong Fundamentals***

Dependent variable	Failure in t+1						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Run	0.35***	0.25***	0.39***	0.29***	0.36***	0.44***	0.36***
	(0.053)	(0.043)	(0.056)	(0.052)	(0.051)	(0.091)	(0.064)
Fundamentals		-2.93***					
		(0.72)					
Fundamentals × Run		-13.5***					
		(1.85)					
Strong Fundamentals			-0.0071***	-0.0034**	-0.0039***	-0.026***	
			(0.0025)	(0.0015)	(0.0011)	(0.0088)	
Strong Fundamentals × Run			-0.29***	-0.26***	-0.23***	-0.44***	
			(0.063)	(0.045)	(0.066)	(0.092)	
Surplus/Equity							-0.012***
							(0.0041)
Noncore funding							0.31***
							(0.088)
Surplus/Equity × Run							-0.29***
							(0.098)
Noncore funding× Run							1.94***
							(0.39)
Observations	328421	279572	279572	75499	241642	37930	327740
R^2	0.060	0.12	0.065	0.098	0.075	0.055	0.094
Mean dep. var.	0.0076	0.0082	0.0082	0.0049	0.0049	0.029	0.0076
Sample	1865-1934	1865-1934	1865-1934	Large Banks	No Crisis	Banking Crisis	1865-1934

Notes: This table presents estimates of Equation (3). Driscoll-Kraay standard errors in parentheses. *,**, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

90th percentile. A run on a weak bank is associated with a 42% probability of failure. A run on a strong bank is associated with only a 12 percentage point probability of failure. Thus, having strong fundamentals substantially reduces the probability of failure when a bank is exposed to a run.

We view this estimate as the upper bound on the likelihood that a run causes the failure of a healthy bank. The reason is that $\text{Fundamentals}_{b,t-1}$ can only proxy for bank health. It cannot capture episodes where a bank was insolvent but had not yet recognized losses (e.g., due to an unexpected shock or fraud). In these cases, news about a bank's trouble that is not yet reflected in bank balance sheets would trigger a run and failure, but the run is a response to a signal of insolvency.[13]

Column 4 zooms in on large banks, defined as banks in the top quartile of total assets. We focus on large banks, as bank distress episodes are more likely to be accurately reported in newspapers for the largest banks. Runs are more likely to be underreported for small banks, especially if they do not result in failure, leading to an upward-biased

[13]Correia et al. (2025) document that failed national banks had both low recovery rates and low asset quality according to OCC bank examiners. Correia et al. (2025) argue this suggests that the vast majority of failed banks were fundamentally insolvent, unless one assumes large value destruction from receivership itself.

estimate of the likelihood that a run results in failure for small banks. This concern is less severe for large banks. In the sample of large banks, we see that a run is associated with a 32% probability of failure for a bank with weak fundamentals, but only a 3% probability of failure for a bank with strong fundamentals. Thus, for large banks, strong fundamentals appear to fully insulate a bank from the risk of failure in response to a non-fundamental run.

Columns 5 and 6 show that these patterns are qualitatively similar during and outside of banking crisis years. Moreover, during crises, having strong fundamentals reduces the likelihood of failure following a run from 48% to around 0%.

Finally, column 7 in Table 5 interacts Run_{bt} with the underlying proxies of solvency and noncore funding. Banks subject to runs are significantly less likely to fail both when they have higher surplus profit-to-equity and when they are less reliant on noncore funding.

Figure 6 presents a visualization of the likelihood that a run leads to failure across the distribution of bank fundamentals. For each decile d of $\text{Fundamentals}_{bt-1}$, we estimate

$$\text{Failure}_{bt} = \beta_0^d + \beta_1^d \text{Run}_{bt} + \epsilon_{bt}, \quad d = 1, ..., 10, \tag{4}$$

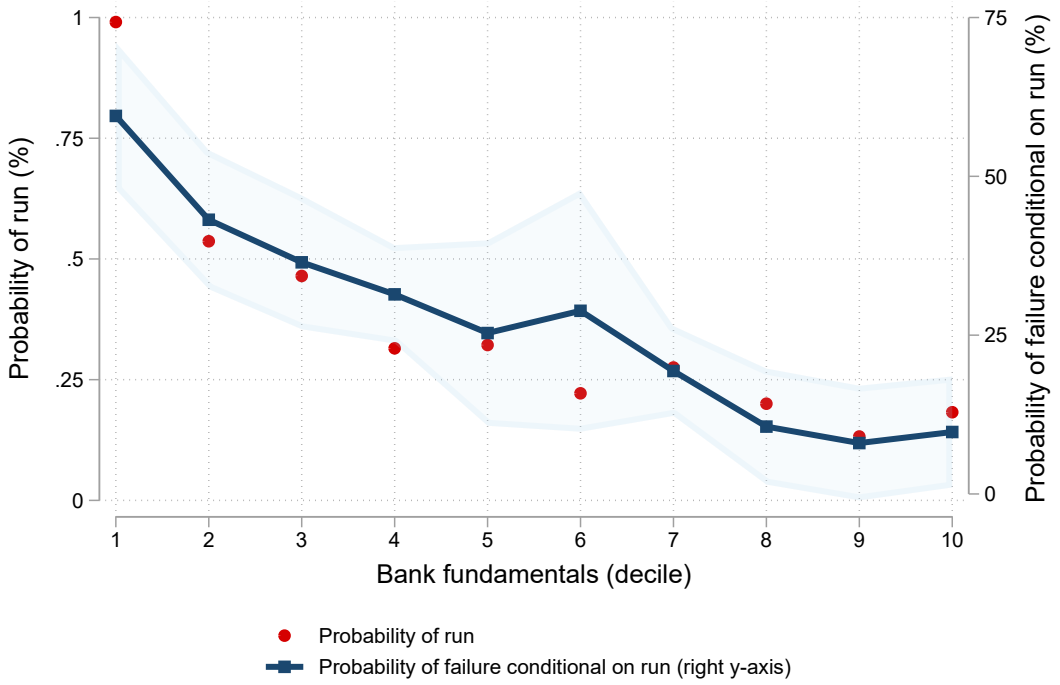
and plot the estimated coefficients $\{\hat{\beta}_1^d\}$. The figure shows that runs are associated with a nearly 70% probability of failure in the banks in the lowest decile of observable fundamentals. The probability of failure following a run falls nearly monotonically for banks with stronger fundamentals. For banks in the strongest decile of our proxy for fundamentals, the probability of failure during a run falls to below 10% and is only borderline statistically significant.

Overall, this evidence indicates that, while runs can occur for strong and weak banks, they are substantially more likely to occur in weak banks. Moreover, conditional on a run, a weak bank is much less likely to survive the runs. Thus, the combination of these two findings indicates that runs almost never trigger the failure of strong banks.

4.3 Event Study of Runs and Failures

To further understand the differences between banks subject to runs without failure, banks subject to runs that fail, and banks that fail without a run, we perform a simple event study comparing the evolution of average bank characteristics around various event

Figure 6: *Probability of Bank Failure Conditional on Being Subject to Run by Bank Fundamentals*



Notes: This figure plots the likelihood of a run (left y-axis) and the probability of failure conditional on a run (right y-axis) across deciles of bank fundamentals. The probability of failure conditional on a run is the coefficients from estimating Equation (4) for each decile of the distribution of Fundamentals$_{bt-1}$. Fundamentals$_{bt-1}$ is a proxy of bank health (see text). The sample consists of all national banks from 1863 through 1934. Shaded area represents 95% confidence intervals based on Driscoll-Kraay standard errors.

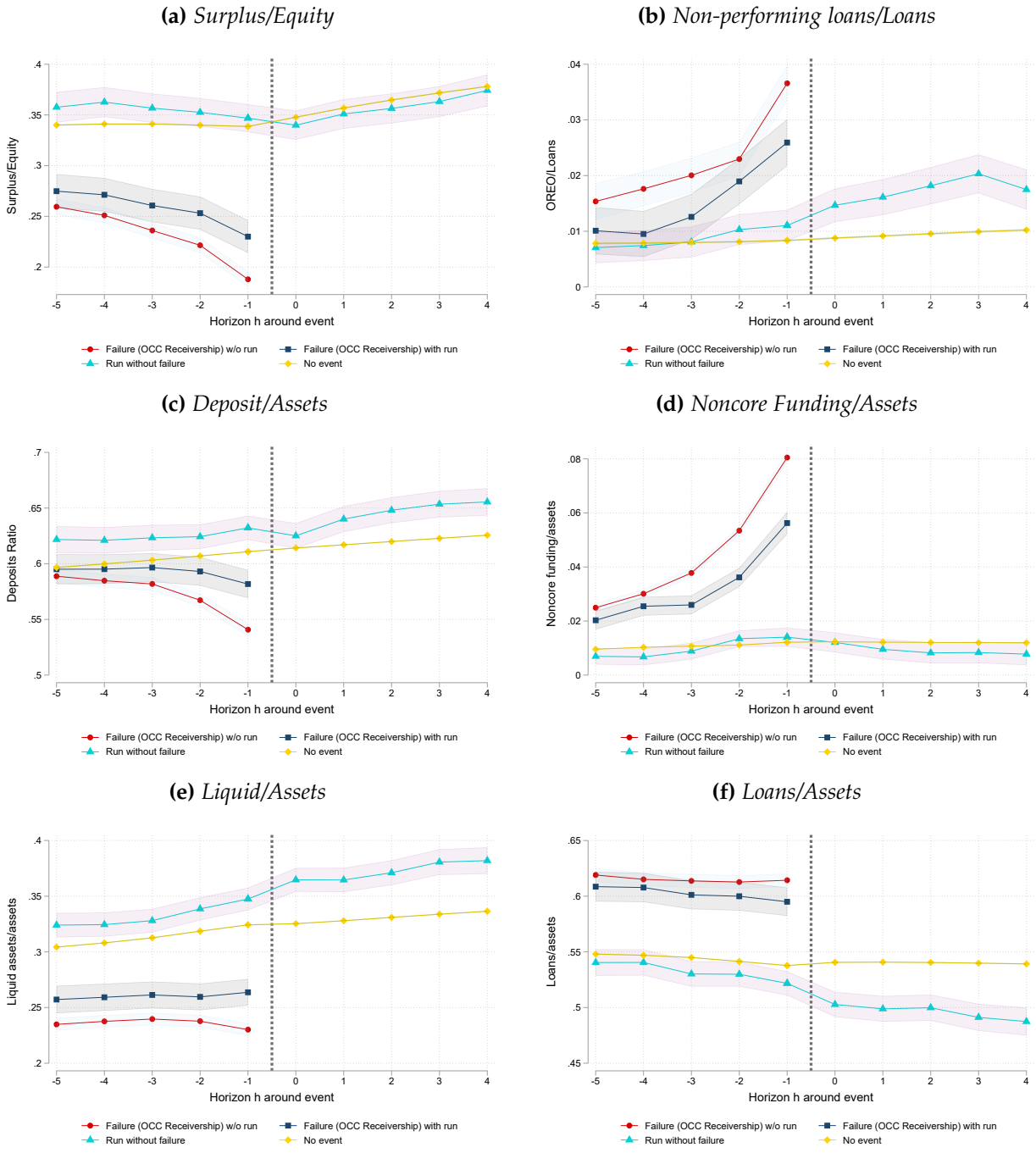
types. Specifically, we estimate specifications of the following form:

$$\begin{aligned} y_{bt+h} = {} & \beta_1^h \times \mathbf{1}[\text{Run w/o failure}_{bt}] \\ & + \beta_2^h \times \mathbf{1}[\text{Failure with run}_{bt}] \\ & + \beta_3^h \times \mathbf{1}[\text{Failure w/o run}_{bt}] \\ & + \beta_4^h \times \mathbf{1}[\text{No Event}_{bt}] \\ & + \gamma_t^h + \epsilon_{bt+h},, \qquad\qquad h = -5, ..., 5. \end{aligned} \tag{5}$$

The dependent variable y_{bt+h} is a bank-level variable in year t. The right-hand-side variables are four mutually exclusive indicator variables: (i) bank is subject to a run in t but does not fail, (ii) bank fails with a run mentioned in newspaper accounts, (iii) bank fails without a run in t, and (iv) no event for bank b in year t. γ_t is a year fixed effect. We exclude the constant term, so the estimated coefficient is the average level of y_{bt+h} around the event. Because a bank that fails does not report bank fundamentals after

failure, coefficients for failure are only estimated for $h = -5, .., -1$. Again, we focus on the sample of all national banks from 1863 to 1934.

Figure 7: ***Characteristics of Banks Subject to Runs With and Without Failing***



Notes: This figure plots the coefficients from estimating Equation (5). Non-performing loans are proxied by the line item "other real estate owned" (OREO). Shaded areas represent 95% confidence bands. Figure A.4 shows the same plot using the deposit, loan, assets, and liquid assets grwoth as the outcome variable.

Figure 7 plots the coefficients from estimating Equation (5) using different metrics of

bank fundamentals, y_{bt}. The figure shows that the strongest differences in fundamentals are across failing and surviving banks, rather than whether a bank is subject to runs. Panel (a) Figure 7 uses surplus-to-equity, our proxy of bank capitalization, as the outcome. Failing banks have a substantially lower level of surplus-to-equity before failure compared to banks subject to a run without failure and banks not subject to any distress event. Moreover, failing banks see a significant deterioration in this capitalization metric in the five years before failure. The difference holds whether or not failure involves a run. Banks that fail with a run are similarly weak on this observable as banks that fail without a run. This helps understand why failures with runs are nearly as predictable as failures without runs, as we saw in Table 4. In contrast, banks that experience a run without failing have a similar level and evolution of capitalization as other banks not subject to a distress event.

Panel (b) of Figure 7 shows a similar pattern for non-performing assets. We proxy non-performing assets by the line item "other real estate owned," which typically reflects seized real estate collateral following borrower default. Failing banks experience a rise in non-performing assets before failure. The rise in non-performing assets holds for banks that fail both with and without a run. Credit losses thus often play an important role in bank failures, both with and without runs.

In panel (b), we also see that banks subject to run without failing do not exhibit this pre-trend in non-performing assets. These banks look similar to banks without exposure to any form of distress event. Banks subject to runs do, however, see an increase in non-performing assets after the run. There are two potential explanations for this finding. One is that a run occurs when there is a public signal that banks will face future losses, so runs predict, but do not cause, future losses (Calomiris and Gorton, 1991). Another possibility is that the run causally increases non-performing assets by causing a deterioration of the local economy.

Panel (c) in Figure 7 shows that failing banks face a decline in their deposit-to-assets ratio of about 4 points before failure.[14] Panel (d) shows that this deposit outflow in deposits is mirrored by an increased reliance on noncore funding in the years before failure. The decline in deposit funding and the rise in noncore funding in the years before failure are similar across banks that fail with and without a run.

Panels (c) and (d) further show that, in contrast to failing banks, banks that are subject to a run without failing do not exhibit a decline in deposits or an increased reliance on noncore funding in the years before the episode. This is another indication that these

[14]Note that banks that fail with a discussion of a run in newspapers see a larger deposit outflow from time -1 to 0 (Figure A.5d). This suggests that the run discussed in newspaper accounts reflects an acute episode of depositor withdrawals, which is precisely the type of episode that would be likely to garner media attention. This decline in deposits for failing banks subject to runs is not shown here.

banks do not appear substantially worse than the average bank on observables. These episodes do, however, lead to a decline in deposits/assets after the run, as expected and explored further below.

Finally, panels (e) and (f) reveal striking differences in liquid assets and loan-to-asset ratios across failing and surviving banks. Failing banks have significantly lower liquid asset ratios and significantly higher loans-to-assets, indicating a riskier investment mix. Before the event, banks that are run without failing look similar to the average bank that is not exposed to a distress event. After a run, surviving banks reduce their loans-to-assets and increase liquid assets-to-assets.

Taken together, failing banks have very different observable characteristics than banks subject to runs that do not fail. Banks subject to runs that do not fail look similar to ordinary banks not subject to any form of distress. Moreover, failing banks are approximately equally weak on observables, irrespective of whether they are subject to a run before failure.

This evidence has three interesting implications. First, it reinforces the result that runs that do not result in failure tend to occur in healthy banks. Second, poor fundamentals are key to determining whether a bank will fail. Third, focusing on bank failures, we do not find clear evidence that runs trigger the failure of relatively healthier banks, on the margin, as observables are similar for banks that fail with and without a run. This suggests that banks that fail with a run might have failed even in the absence of the run. The run was merely the immediate trigger determining the timing of failure.

5 Consequences of Runs and Failures

This section studies the consequences of bank distress episodes. We first study the impact of bank runs on surviving banks at the bank level. Next, we study the impact of bank runs and failures for the local economy.

5.1 Bank-Level Impact of Bank Runs Without Failure

What are the consequences of bank runs without failure at the bank level? To answer this question, we estimate simple local projections of the following form:

$$\frac{Y_{bt+h} - Y_{bt-1}}{\text{Assets}_{bt-1}} = \alpha_b + \gamma_t + \beta^h \text{Run}_{bt} + \epsilon_{bt+h}, \quad h = -5, \ldots, 5 \tag{6}$$

with the prediction horizon h running from five years before to five years after the distress episode. Run_{bt} is an indicator variable equal to one for a bank run without failure. We measure the change in a given bank balance sheet item ($Y_{b,t+h} - Y_{b,t-1}$) relative to total assets in the year before the event, $\text{Assets}_{b,t-1}$, so all magnitudes are relative to total pre-event assets. α_b is a bank fixed effect, and γ_t is a year fixed effect to control for aggregate shocks.

Before presenting the results, we note that we are cautious in our interpretation of this regression. Runs without failure may result in a contraction in lending through a reduction in bank credit supply. However, a run without a failure can also occur in response to bad news about the economy that leads depositors to run as a precautionary measure and simultaneously reduces demand for loans and deposits. Without an instrument for an "exogenous" run, for now, we can only interpret this evidence as descriptive.

Figure 8a shows the results for deposits and loans for the entire 1865-1934 sample of national banks. There is no pre-trend before a run without failure in either deposits or loans. Once a bank is exposed to a run, deposits decline by around 7.5 percent as a share of pre-event assets and remain depressed thereafter. Loans decline by a similar magnitude. Thus, while we have selected episodes of bank distress that do not result in failure, these are still associated with a decline in deposits and loans. Figure A.6 in the Appendix also shows estimates for various other line items such as total assets, loans, and liquid assets. The main shifts following a run are a decline in total deposits and loans. Interestingly, we do not observe an increase in non-deposit financing to offset the reduction in deposits following a run. However, this may in part be a reflection of the fact that our data are annual and not picking up short-term borrowing via the interbank market as is common during times of distress (see, e.g., Afonso et al., 2011; Blickle et al., 2024).

Figure 8b explores heterogeneity across distress episode types. "Run-only" episodes in which the bank is run but does not suspend have the mildest reductions in deposits. After these episodes, banks fully recover their deposits within five years. Episodes with a run, suspension, and reopening are the most severe, leading to a 20 percent decline in deposits that persists for five years.

What are the implications of a run without failure across weak and strong banks? To

answer this question, we estimate local projections of the form:

$$\begin{aligned}\frac{Y_{b,t+h} - Y_{b,t-1}}{\text{Assets}_{b,t-1}} = \alpha_b + \gamma_t &+ \beta_S^h \text{Run}_{b,t} \times \text{Strong Fundamentals}_{b,t-1} \\ &+ \beta_W^h \text{Run}_{b,t} \times \text{Weak Fundamentals}_{b,t-1} \\ &+ \epsilon_{b,t+h}, \qquad h = -5, \ldots, 5\end{aligned} \tag{7}$$

where strong (weak) fundamentals are defined as being in the top (bottom) tercile of our fundamentals measure in $t-1$.

Figure 8 panels (c) and (d) present the results. Runs without failure lead to larger deposit declines for banks with weak fundamentals. Banks with strong fundamentals nearly recover their lost deposits within five years, whereas banks with weak fundamentals see a persistent decline in deposits. The decline in lending is also stronger for banks with weak fundamentals. Thus, weak fundamentals also shape the consequences of bank runs when banks survive runs.

5.2 Regional Consequences of Runs and Failures

We next examine the consequences of bank runs and failures at the regional level. There is considerable time-series and cross-sectional variation in state-level exposure to bank distress episodes (Figure A.8). In most years, the typical state has no bank distress episode, even during banking crisis years. During those years, the number of episodes spikes in the upper tail of the distribution. At the same time, even in a crisis year, many states do not have bank distress episodes. This indicates that most banking crises from 1863 to 1934 had a strong regional component.

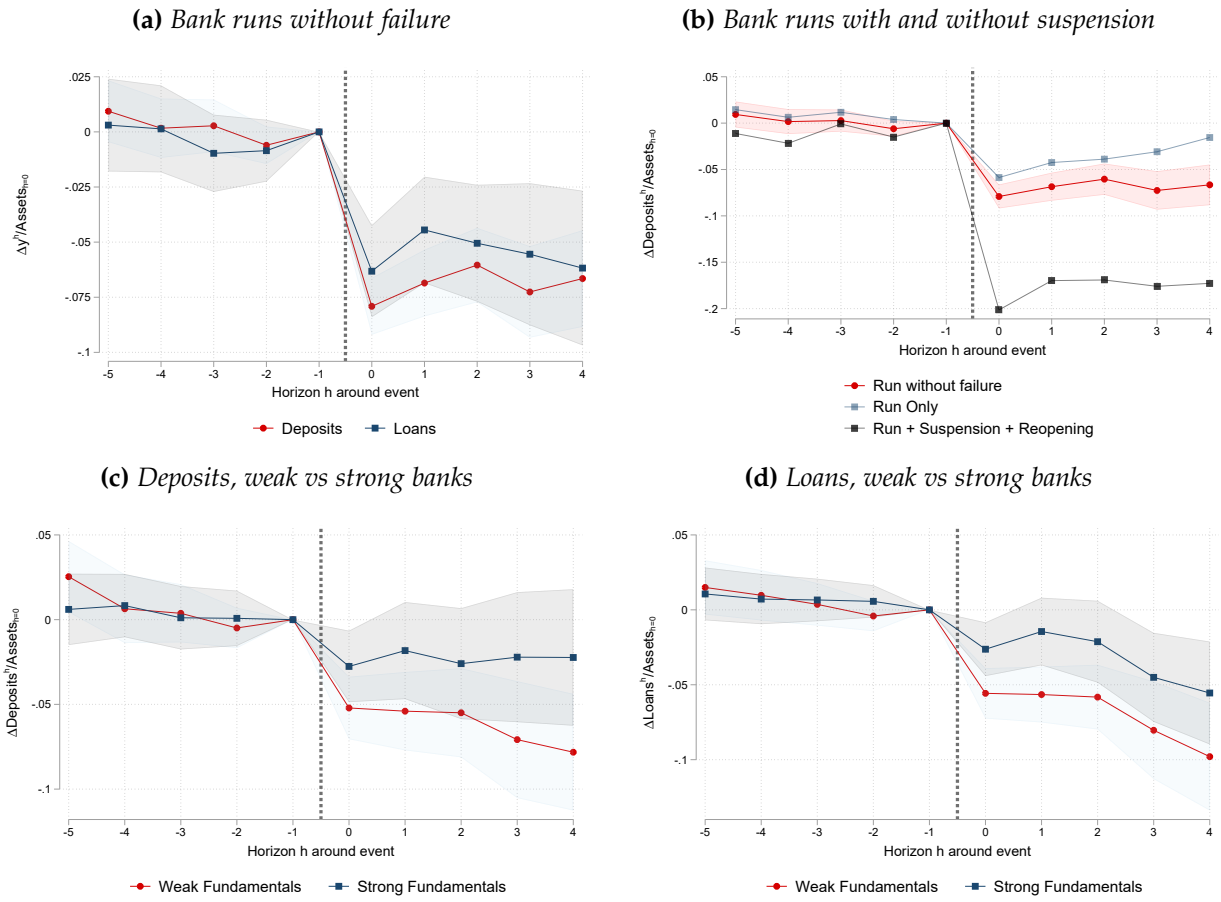
To understand the regional consequences of bank runs and failures, we estimate impulse responses from local projections of the following form:

$$\begin{aligned}y_{c,t+h} = &\alpha_i + \gamma_b + \beta_0^h \text{Distress Exposure}_{c,t} \\ &+ \sum_{l=1}^{L} \left[\delta_l^h y_{c,t-j} + \beta_l^h \text{Distress Exposure}_{c,t-l} \right] + \epsilon_{c,t+h}, \quad h = 0, ..., H\end{aligned} \tag{8}$$

where $y_{c,t+h}$ is an outcome such as total lending in region c in year $t+h$. The local projection impulse response is the sequence of estimated coefficients $\{\hat{\beta}_0^h\}$. We include lags of both the shock and the dependent variable, as is standard in the local projections framework (Jordà, 2005).

The shock, Distress Exposure$_{c,t}$, is the asset-weighted share of banks in a region (city

Figure 8: ***Bank-Level Deposit and Loan Dynamics around Bank Runs Without Failure***



Notes: This figure reports coefficients from estimating Equation (6). Shaded areas represent 95% confidence intervals based on Driscoll–Kraay standard errors.

or state) subject to a particular distress event. Therefore, Distress Exposure$_{c,t}$ ranges from 0 for a region where no banks are exposed to the event in year t to 1 if all banks are exposed. We consider three mutually exclusive bank distress episodes: (i) run without failure, (ii) failure without a run, and (iii) failure with a run. This allows us to separate episodes that are closer to pure liquidity events from episodes involving bank insolvency.

We conduct the analysis at both the city and state levels. At the city level, $y_{c,t}$ is based on the aggregate of national bank balance sheets. At the state level, we consider both aggregated national bank balance sheets and the digitized "All Banks Statistics" from Flood (1998), which includes state banks. The latter is available starting in 1896.

Figure 9 presents the results for loans and deposits at the city and state level. At both the city and state level, failures translate into substantially larger deposit and lending contractions than runs without failure. Runs without failure lead to a small and temporary decline in deposits that recovers after a few years. The effect on loans is more

persistent but modest in size. Thus, bank distress involving bank failure is associated with substantially worse lending contractions than episodes with runs that do not result in failure. Failures, which are related to bank insolvency, are necessary for bank distress to involve severe local deposit and lending contractions.

Figure 9 further shows that failures with runs lead to slightly worse declines in loans and deposits compared to failures without runs. Thus, runs may exacerbate distress in the local banking system. This distinction is especially true in the short run. In the medium term, the consequences of failures with and without runs are equally severe.

In terms of magnitudes, Figure 9 shows that if 10% of a city's banks fail without a bank run, total deposits will decline immediately by around 6% and loans will fall by around 10%. In contrast, if 10% of all banks fail with a bank run, deposits will decline by around 10% and loans by 15%. In both cases, the effect is somewhat persistent, although there is a slight recovery. After 5 years, total loans will remain around 5% lower for both types of distress events. In contrast, if 10% of all banks are subject to a run but do not fail, both deposits and loans decline by only 2%. While deposits fully recover after four years, loans remain below trend.

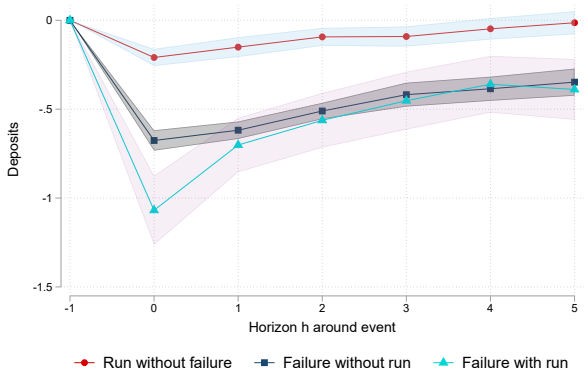
6 Concluding Remarks

In this paper, we apply natural language processing to historical newspapers to study episodes of bank distress involving bank runs, suspensions, and failures in the United States from 1863 to 1934. Our novel data covers thousands of incidents of bank runs. Combined with balance sheet information on banks, these data allow us to derive several important insights.

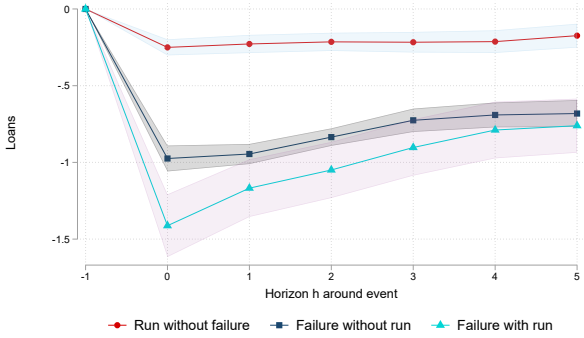
We establish that runs without failure were common before deposit insurance. Moreover, we show that runs are more likely in relatively weaker banks, broadly in line with (Goldstein and Pauzner, 2005). We also show that runs on otherwise healthy banks were not uncommon in the historical US banking sector, even if they were less likely than runs on weak banks. However, such runs on healthy banks essentially never resulted in failure, contra models in the tradition of Diamond and Dybvig (1983), but more consistent with theories based on asymmetric information or behavioral runs. Furthermore, healthy banks can survive bank runs without any other major consequences, while weak banks that manage to survive runs remain scarred by the run in the medium term. Taken together, our findings thus suggest that poor bank fundamentals are necessary for bank runs to translate into failure and, more broadly, for bank distress to translate into severe economic consequences.

Figure 9: ***Consequences of Runs and Failures at the Local Level***

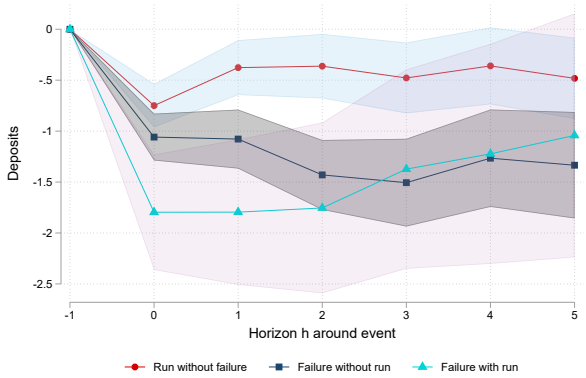
(a) *National bank deposits, city level*



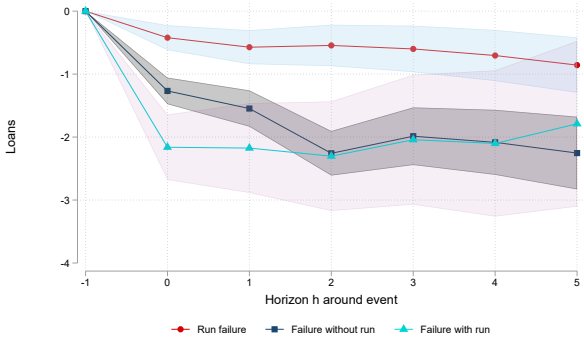
(b) *National bank loans, city level*



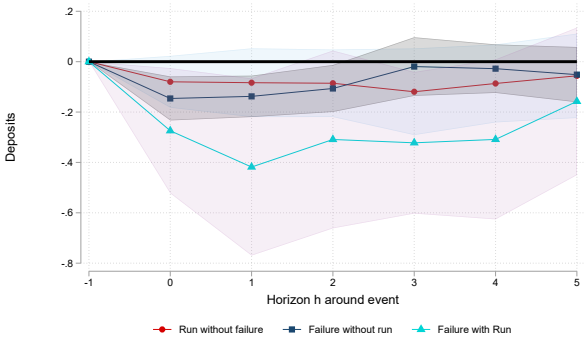
(c) *National bank deposits, state level*



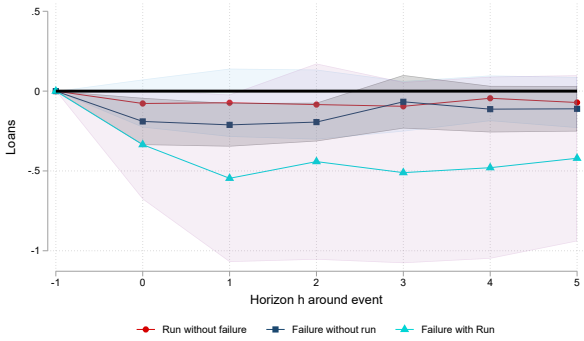
(d) *National bank loans, state level*



(e) *All deposits, state level*



(f) *All loans, state level*



Notes: Panel (a) through (d) are based on sample of national banks from 1863-1934. Data in panel (e) and (f) are from All Bank Statistics are digitized by Flood (1998) and cover state-level aggregate deposits and loans from 1896 through 1955.

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Bank Runs, Failures, and the Real Economy

Online Appendix

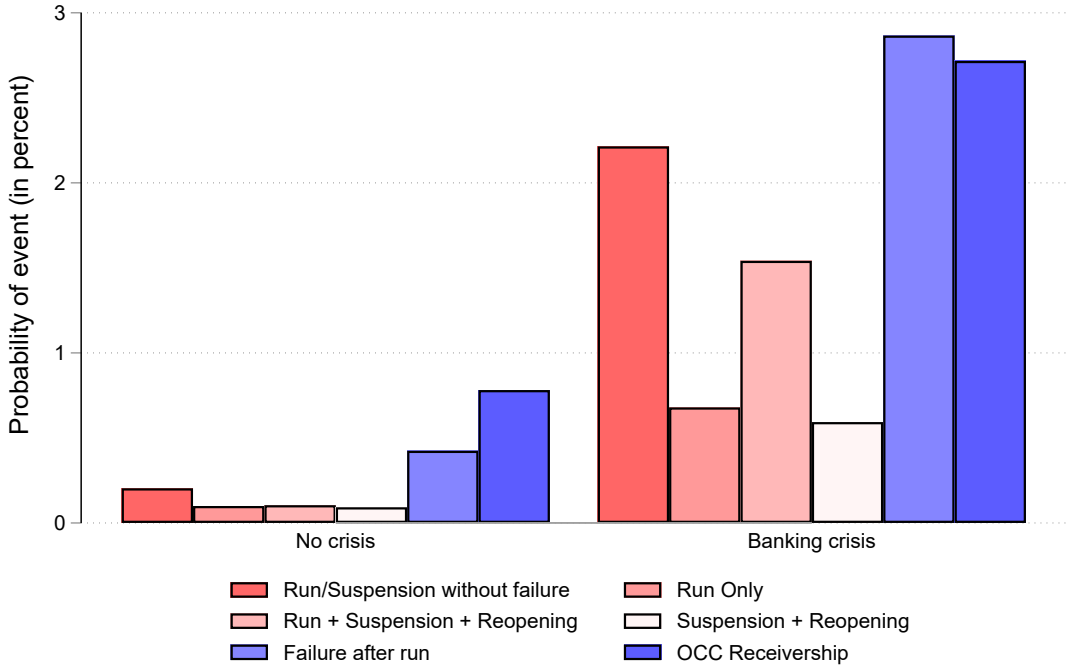
Sergio Correia, Stephan Luck, and Emil Verner*

- Appendix A: Additional Figures
- Appendix B: Additional Tables
- Appendix C: Constructing the Bank Distress Episodes Dataset

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A Additional Figures

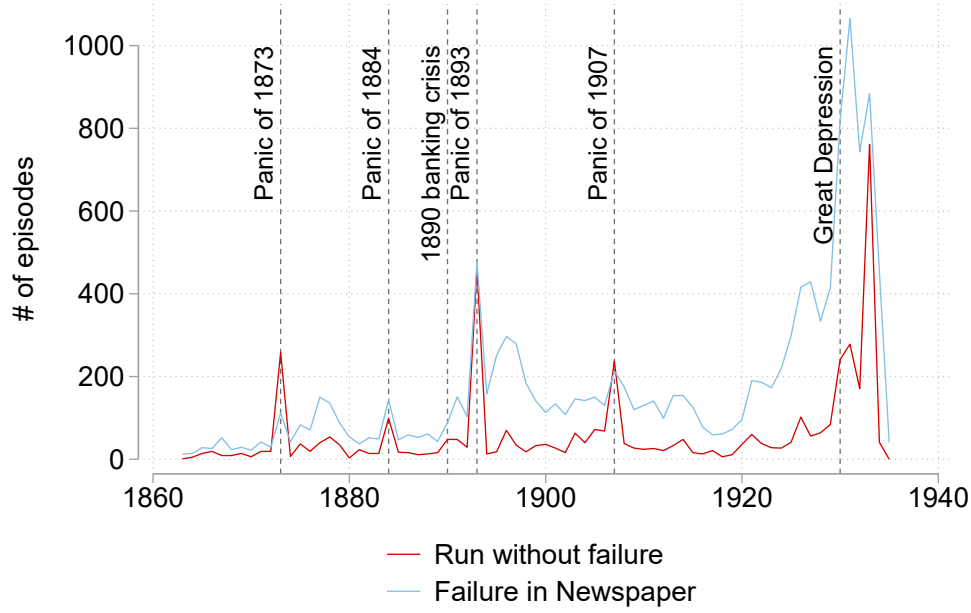
Figure A.1: *Probability of Bank Distress Episodes for National Banks During and Outside of Banking Crises*



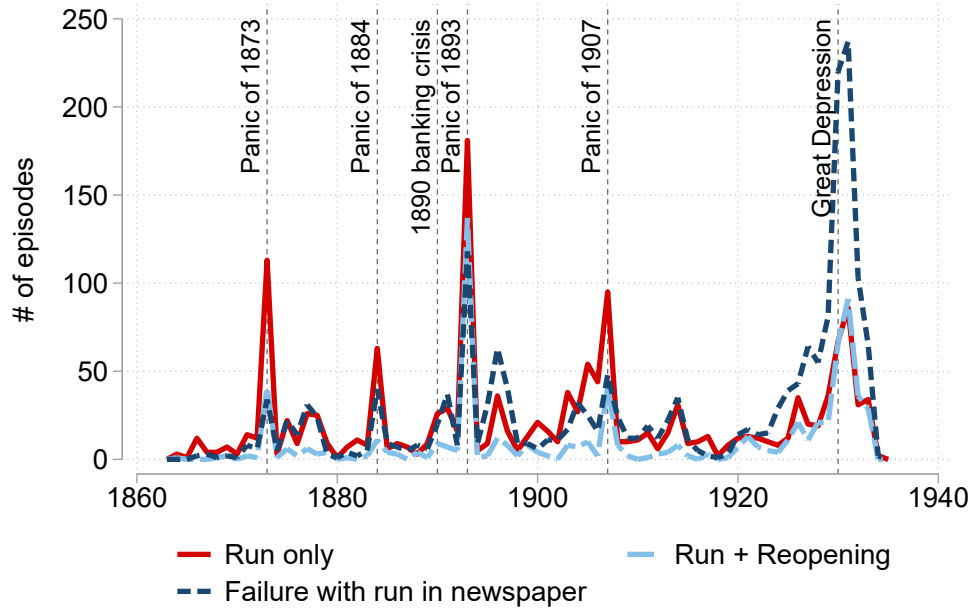
Notes: The figure plots the probability of various bank distress episodes during and outside of years identified as banking crises in Baron et al. (2021). The sample is based on all national banks from 1863-1934.

Figure A.2: ***Bank Distress Episodes in Newspapers from 1863-1935.***

(a) *Runs and failures in newspapers*



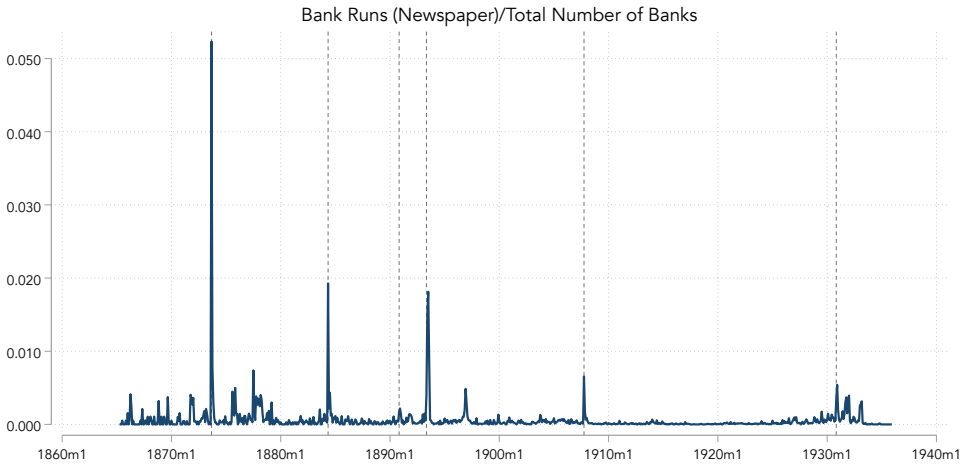
(b) *Events involving runs*



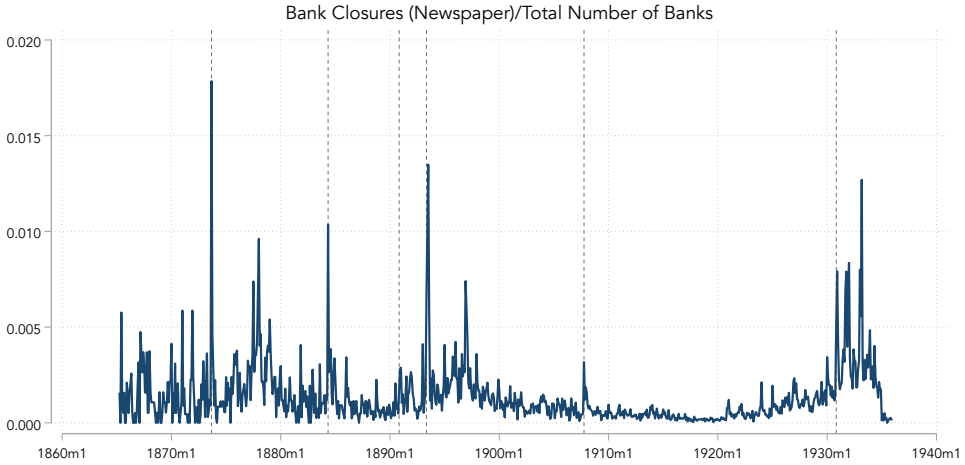
Notes: Panel (a) and (b) are based on the numbers of total bank distress events across all bank types from 1863 through 1934.

Figure A.3: ***Monthly Time Series: Bank Failures and Bank Runs***

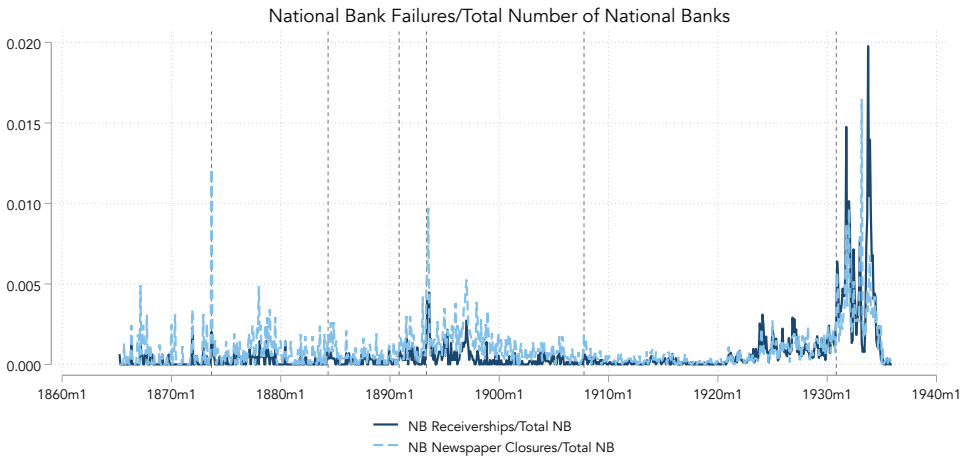
(a) *Bank Runs (in newspapers)*



(b) *Bank Failures (in newspapers)*

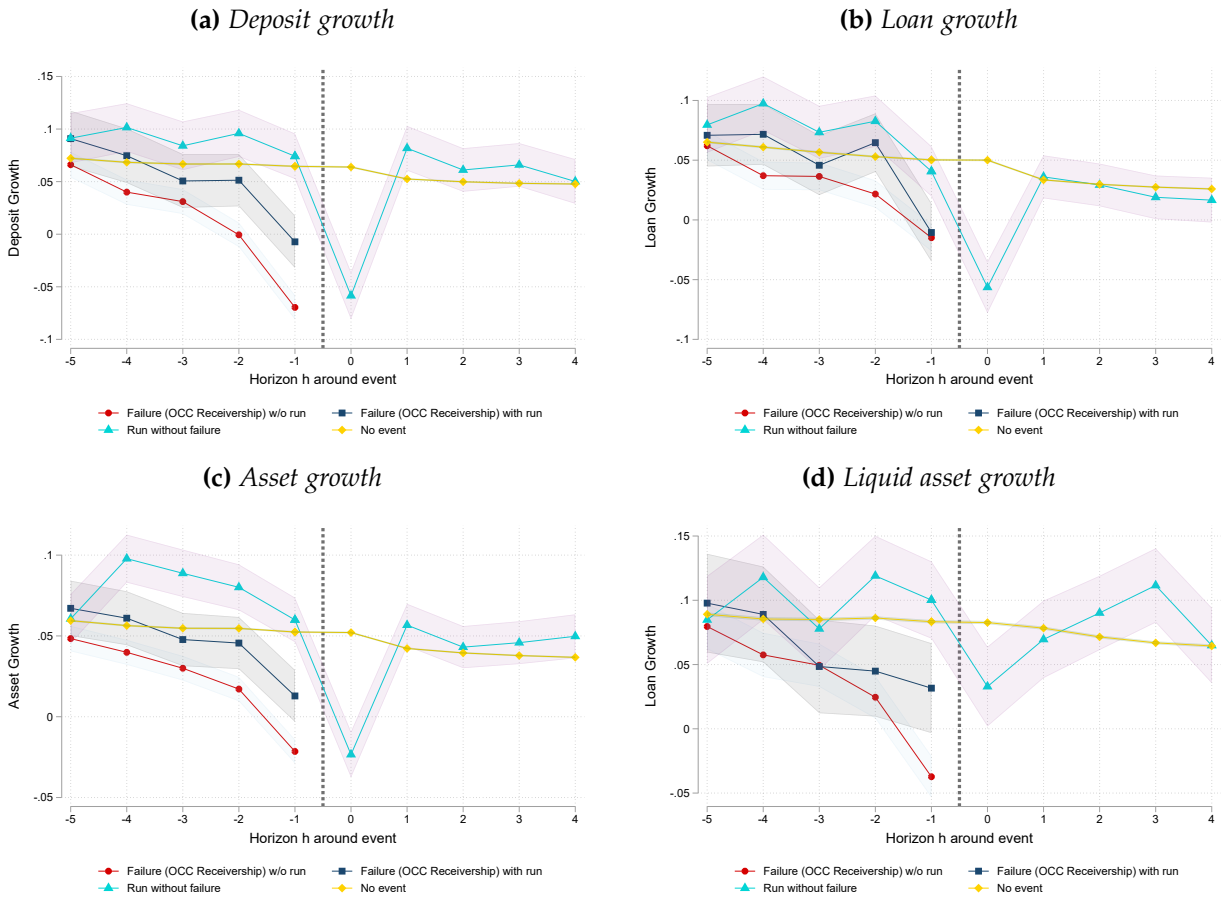


(c) *Bank Failures, National Banks (from OCC and newspapers)*



Notes: Vertical lines represent the month of a banking panic from Baron et al. (2021).

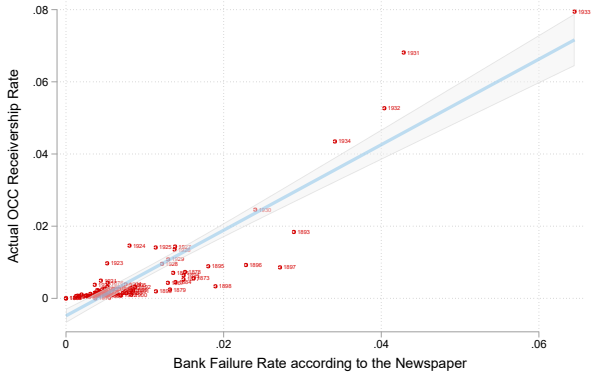
Figure A.4: ***Characteristics of Failing Banks and Banks Subject to Runs that Survive around Distress Events: Growth Rates***



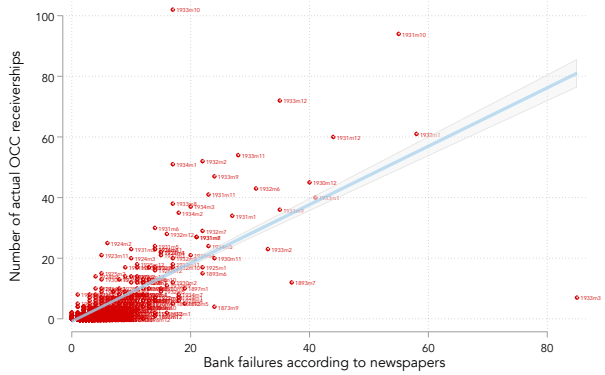
Notes: This figure plots the coefficients from estimating Equation (5). Shaded areas represent 95% confidence bands.

Figure A.5: *Data Quality Validation*

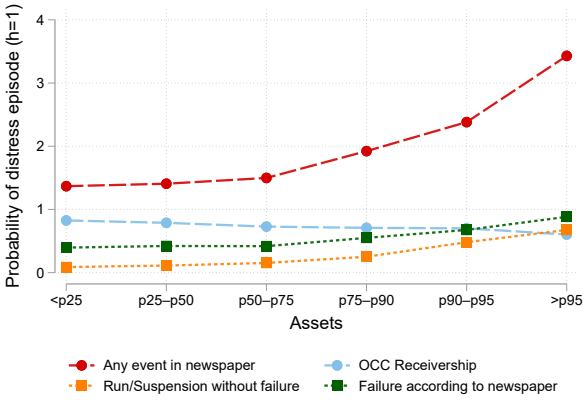
(a) *National Bank Failure Rates: Annual*



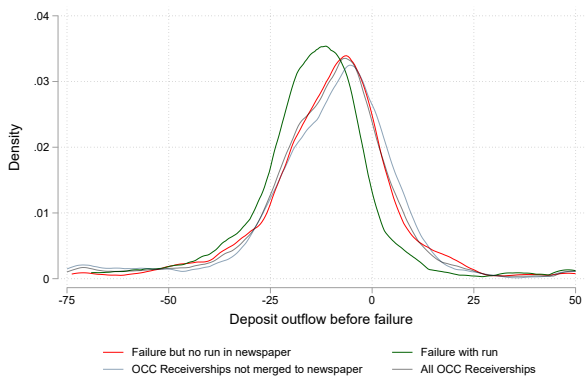
(b) *Number of National Bank Failures: Monthly*



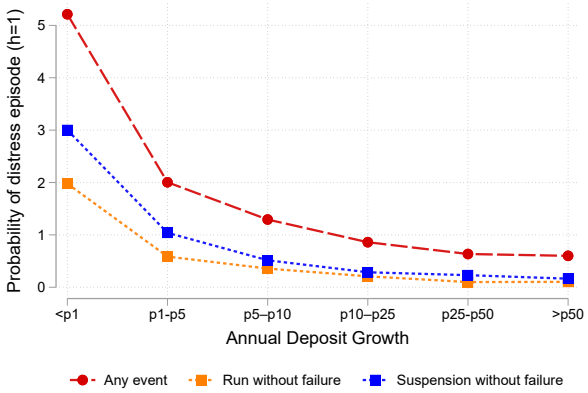
(c) *Events by Size*



(d) *Deposit Outflows*



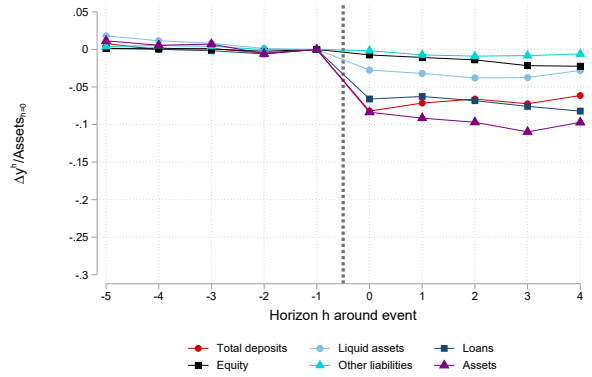
(e) *Probability of distress event as a function of deposit growth*



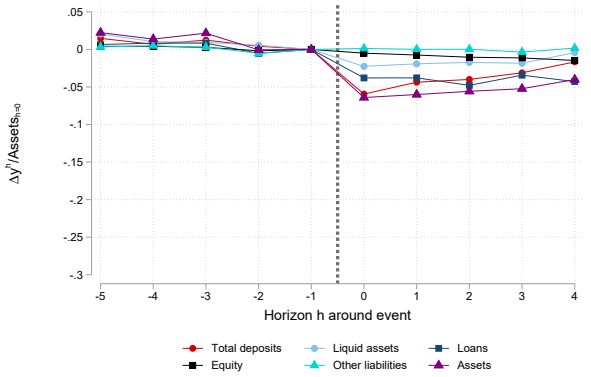
Notes: The sample in all panel is based on national banks during 1863-1934. In panel (d), the sample is all OCC national bank receiverships during 1864-1934. Deposit outflows before failure are calculated using the total deposits reported in the last call report before failure and deposits at failure.

Figure A.6: *Dynamics of Balance Sheets around Bank Runs that Do Not Result in Bank Failure*

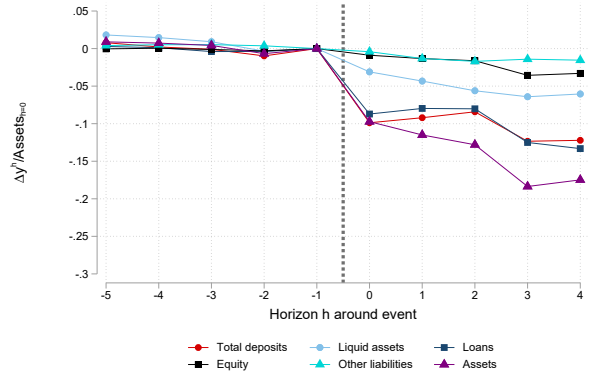
(a) *Bank/suspensions without failure*



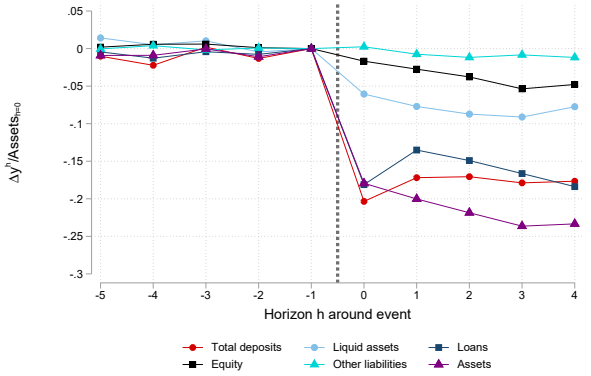
(b) *Bank run only*



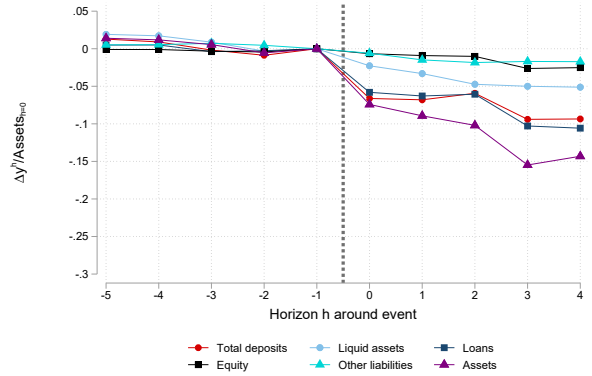
(c) *Suspension without failure*



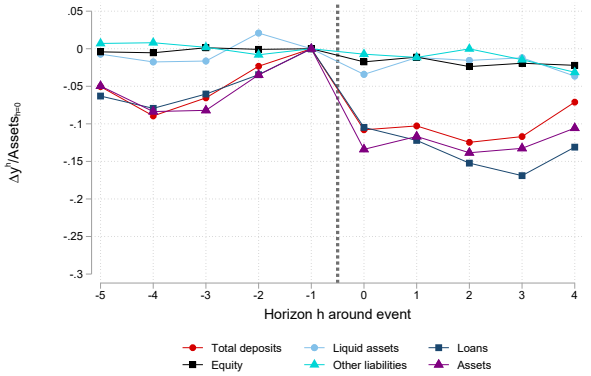
(d) *Run, suspension and reopening*



(e) *Suspension without failure*

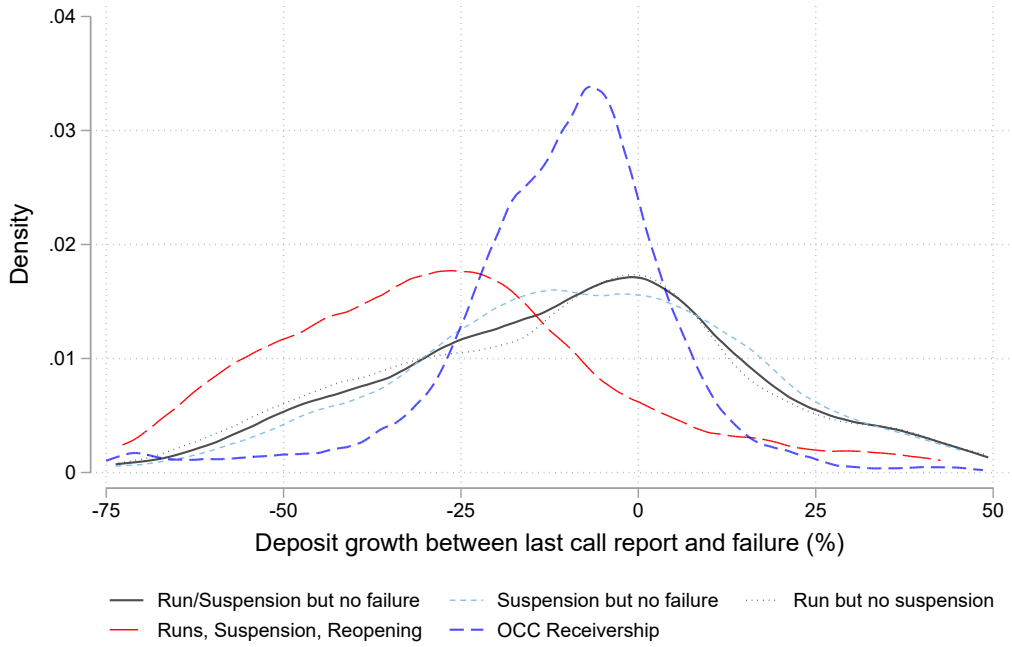


(f) *Run but outcome unsure*



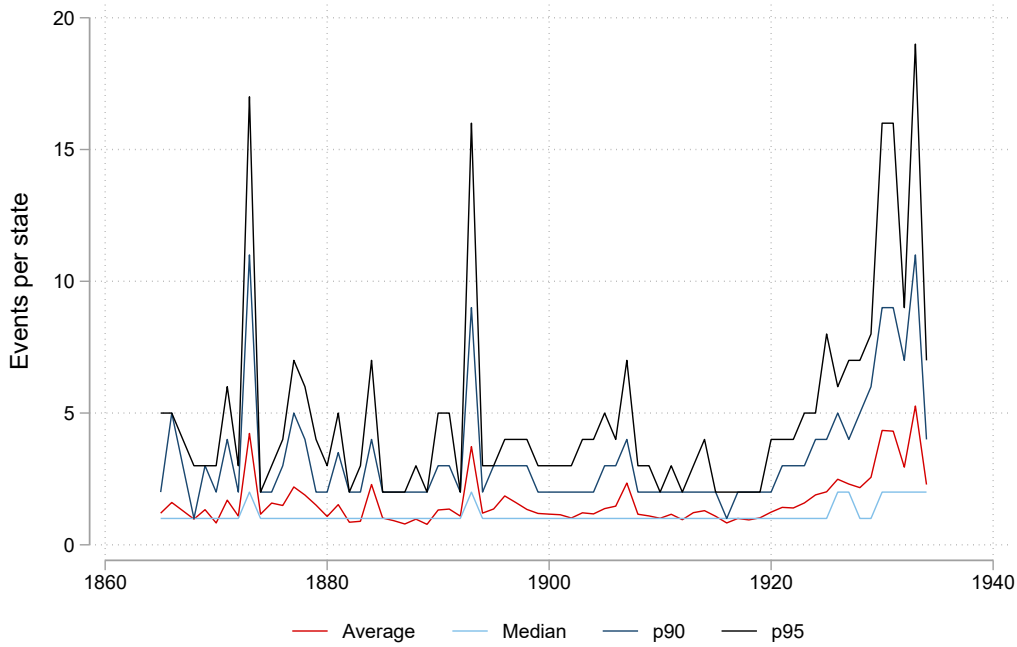
Notes: This figure reports coefficients from estimating Equation (6). Shaded areas represent 95% confidence intervals based on Driscoll-Kraay standard errors.

Figure A.7: *Deposit Outflows Around Distress Events*



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%.

Figure A.8: *Number of Distressed Bank Events in Newspapers per State*



Notes: This figure shows average, median, p90, and p95, of the number of newspaper distress events per state per year.

B Additional Tables

Table B.1: ***Bank Runs, Failures, and Fundamentals: Detailed Specifications***

Dependent variable	Failure in t+1							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Run	0.35***	0.45***	0.27***	0.22***	0.33***	0.29***	0.33***	0.34***
	(0.053)	(0.072)	(0.043)	(0.035)	(0.076)	(0.069)	(0.071)	(0.071)
Surplus/Equity		-0.015***				-0.0065***	-0.015***	-0.025***
		(0.0046)				(0.0013)	(0.0052)	(0.0082)
Surplus/Equity × Run		-0.34***				-0.26***	-0.35***	-0.35***
		(0.11)				(0.097)	(0.078)	(0.077)
Noncore funding			0.31***			0.10***	0.31***	0.26***
			(0.088)			(0.027)	(0.089)	(0.067)
Noncore funding× Run			1.99***			2.14***	1.91***	1.88***
			(0.38)			(0.71)	(0.38)	(0.38)
OREO/Loans				0.10***		0.081***		
				(0.029)		(0.021)		
OREO/Loans× Run				2.08***		1.54**		
				(0.67)		(0.65)		
Liquid/Assets					0.00015	0.0010	0.0096*	-0.022***
					(0.0043)	(0.0015)	(0.0054)	(0.0065)
Liquid/Assets × Run					0.054	-0.26*	0.16	0.13
					(0.15)	(0.15)	(0.12)	(0.12)
Observations	328421	328180	327859	109901	327156	109895	327064	327064
R^2	0.060	0.063	0.092	0.10	0.060	0.13	0.095	0.11
State FE						✓		✓
Year FE						✓		✓
Sample	1865-1934	1865-1934	1865-1934	1865-1904	1865-1934	1865-1904	1865-1934	1865-1934

Notes: Robust standard errors. *,**, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table B.2: ***Bank Runs, Failures, and Fundamentals: Different Time Periods***

Dependent variable	Failure in t+1					
	(1)	(2)	(3)	(4)	(5)	(6)
Run	0.34***	0.30***	0.84***	0.84***	0.37***	0.27
	(0.071)	(0.071)	(0.12)	(0.051)	(0.078)	(0.20)
Surplus/Equity	-0.025***	-0.0052***	-0.020***	-0.090***	-0.011***	-0.050*
	(0.0082)	(0.00096)	(0.0052)	(0.027)	(0.0031)	(0.026)
Surplus/Equity × Run	-0.35***	-0.29***	-0.78***	-0.45***	-0.45***	-0.12
	(0.077)	(0.089)	(0.15)	(0.072)	(0.087)	(0.16)
Noncore funding	0.26***	0.083***	0.23***	0.66***	0.19***	0.79***
	(0.067)	(0.023)	(0.056)	(0.12)	(0.045)	(0.12)
Noncore funding× Run	1.88***	2.29***	0.23	0.72**	1.62***	2.11***
	(0.38)	(0.57)	(0.35)	(0.30)	(0.51)	(0.65)
Liquid/Assets	-0.022***	-0.0020	-0.013***	-0.047***	0.0025	0.028**
	(0.0065)	(0.0014)	(0.0033)	(0.014)	(0.0019)	(0.014)
Liquid/Assets × Run	0.13	-0.11	-0.55*	-0.58***	0.12	0.13
	(0.12)	(0.13)	(0.29)	(0.11)	(0.14)	(0.22)
Observations	327064	173060	116888	37116	284369	42695
R^2	0.11	0.11	0.092	0.16	0.098	0.12
State FE	✓	✓	✓	✓		
Year FE	✓	✓	✓	✓		
Sample	1865-1934	1865-1913	1914-1928	1929-1934	Not BVX Crises	BVX Crises

Notes: Robust standard errors. *,**, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table B.3: ***Deposit Outflows Around Bank Distress Events***

Event Type	Average	Share of failures with deposit growth falling within...						*N*
		<-30%	[-30,-20%)	[-20,-7.5%)	[-7.5,-2.5%)	[-2.5,0%)	>0%	
OCC Receivership	-13.93	0.13	0.12	0.33	0.16	0.07	0.19	2730
Run/Suspension without Failure	-9.62	0.23	0.12	0.16	0.08	0.05	0.37	1054
Suspension but no Failure	-6.27	0.19	0.08	0.13	0.09	0.08	0.43	439
Run without Suspension	-5.52	0.17	0.13	0.19	0.08	0.04	0.39	480
Run, Suspension, Reopening	-35.14	0.53	0.20	0.12	0.04	0.00	0.12	135

Notes: For OCC Receiverships, 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." For other distress events, the table reports the growth in deposits in the call report before and after the start date of an event. Deposit growth is clipped at 100%.

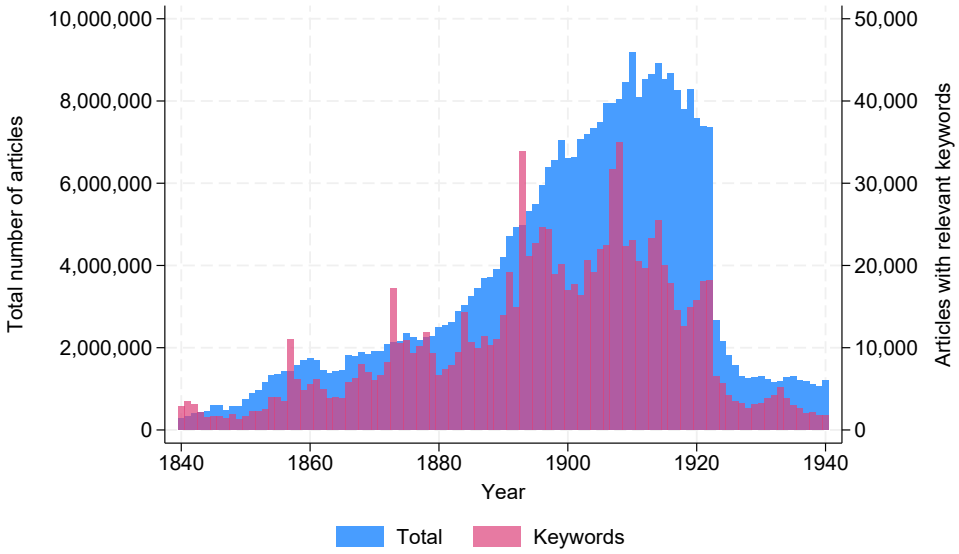
C Constructing the Bank Distress Episodes Dataset

Table C.1: *Selected keywords and rules used to identify articles possibly related to bank distress*

Detection method	Required keywords	Notes
Primary methods: keyword combinations		
Bank Run	`bank` + `run`	Exclude non-financial uses of "run" such as "trains are running".
Bank suspension	`bank` + `suspen` (e.g., suspend, suspension)	Exclude non-financial suspensions, such as "suspension of production" or "rules were suspended."
Bank receivership	`bank` + `receiver` or `assignee` or `assigned`	Private and state banks often used *asignees* rather than *receivers*.
Bank panic	`bank` or `deposit` + `panic`	
Large withdrawals	`deposit` + `large` + `withdraw`	Catches articles describing significant withdrawals without explicitly using the word "run."
Secondary methods: high-confidence phrases		
Specific distress phrases	A specific phrase is present alongside the word `bank`.	Strong indicators of distress with low risk of false positives. Seventeen keywords which include: `"heavy run"`, `"financial stringency"`, `"temporary embarrassment"`, `"heavy withdrawals"`, etc.
Suspension rules	30/60/90-day notices + `deposit`	Allow for spelling variants: “thirty days”, “60 days”

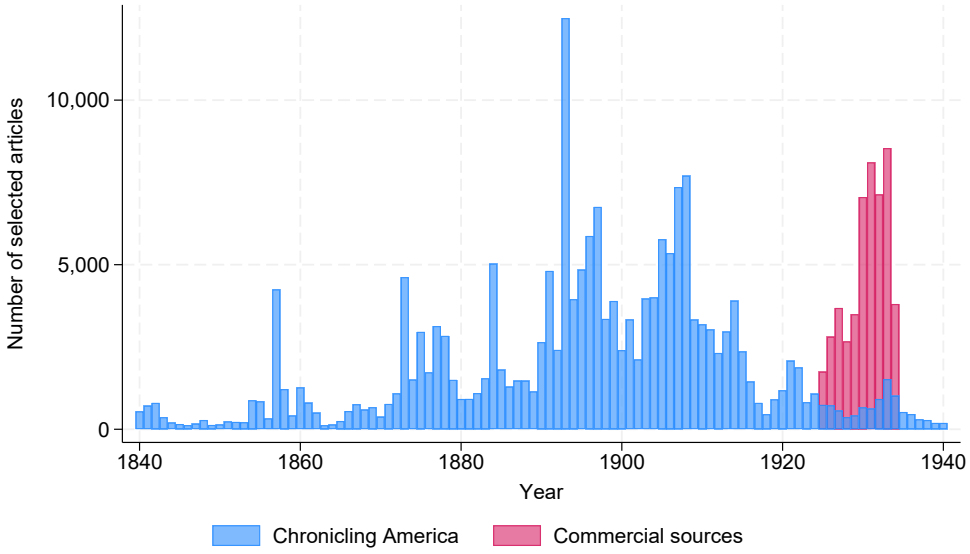
Notes: Matching is case-insensitive. To avoid false positives, unrelated words are first removed from the text before searching. These include geographical features (e.g., “river bank”, “snow bank”), proper names (e.g., “Albert Banks”), and common but unrelated financial terms (e.g., “bank loans,” “banknote”). Any rule involving the keyword `bank` is also repeated for the keyword `trust co`.

Figure C.1: *Total Number of Newspaper Articles from Chronicling America*



Notes: The left axis depicts total articles available per year in "Chronicling America", while the right axis shows the number of articles with keywords related to bank distress events (see Appendix Table C.1). The scale of the left axis is 200 times larger than that of the right axis. On average across the sample, 3% of all articles have matching keywords. To identify the articles available in each newspaper page, we use the "American Stories" dataset (Dell et al., 2023), which segments all pages into articles and obtains the text of each article using a simple but scalable OCR.

Figure C.2: *Number Newspaper Articles Used in Final Sample*



Notes: This figure shows the number of newspaper articles per year included in our final sample of newspaper articles. The two requirements for inclusion are i) having at least one keyword related to bank distress events (see Table C.1) and ii) being flagged by an LLM as related to a bank distress event (see Appendix C.1). This last step minimizes the number of articles related to foreign bank runs, hypothetical bank runs—for instance, "runs to the bank of the river"—that appear in our sample. We rely on "Chronicling America" for most of the sample period, and complement it with commercial sources for 1925-1934.

C.1 LLM Prompts Used in the Data-Constructing Process

```
Below is the text of an old historical newspaper article that contain many OCR
 errors.

Return True if the article could be describing any of the following events in
relation to a U.S. bank: a bank run, bank panic, bank failure, bank closing,
bank reopening, deposit suspension, panic among depositors, or any similar
banking crisis or issue. Otherwise, return False.

Notes:

- Again, if the article discusses foreign banks (banks located outside the
United States) you must return False.
- If you believe the article might involve one of those issues listed above
for U.S. banks (bank runs, etc.), return True, and False if not.
- If you are unsure, return True.

Text:

{article_text}
```

Listing C.1: ***Quick LLM.*** *Prompt used to discard obvious false positives, such as articles discussing foreign banks, hypotheticals, or other unrelated content.*

```
You are an expert research assistant specializing in historical U.S. banking
events. Analyze the provided digitized newspaper article, keeping in mind
possible OCR errors.

# Task

Identify if the article references any of these historical U.S. banking events
:

- Bank run
- Bank suspension
- Bank reopening/resumption
- Bank receivership

Only consider actual events involving U.S. banks or trust companies. Exclude:

- Foreign banks (e.g., Canadian, English, Australian)
- Hypothetical, fictional, or purely general mentions of panic without
concrete events
```

```
16
17 Historical synonyms to recognize include variations of:
18
19 - Runs: "run on the bank", "heavy withdrawals", "steady withdrawals", "
   temporary embarrassment", "invocation of the 30-day rule", "undue excitement",
    "drain upon cash"
20 - Suspensions: "failure to open", "temporarily closed"
21 - Reopenings: "resumption", "resumed operations"
22 - Receiverships: "assigned a receiver"
23
24 # Response format
25
26 {{
27   "is_match": boolean,
28   "events": [
29     {{
30       "event_type": "run" | "suspension" | "reopening" | "receivership" | "
   other",
31       "bank_type": "national" | "state" | "private" | "unknown",
32       "date": "YYYY-MM-DD" (ISO 8601, or partial like "1909-12-00", or null),
33       "bank_name": string,
34       "state": two-letter state code or null,
35       "city": string or null,
36       "cause": string describing reason(s) or null,
37       "snippet": direct article excerpt or null,
38       "measures": measures to address liquidity (for runs) or null
39     }}
40   ]
41 }}
42
43 # Important Guidelines
44
45 - If the article does not describe any relevant U.S. banking event, set `
   is_match` to False and return an empty list for events.
46 - Represent each distinct bank and event separately; do not combine multiple
   banks or events. If a given event lists multiple banks, treat it as multiple
   events. If the article discusses multiple events, such as a bank and
   subsequent closure, treat them as multiple events and list them separately.
47 - Handle unclear or missing information due to OCR errors:
48   - Provide your best interpretation or set fields as null if uncertain.
49   - **Do not invent or infer unsupported details.**
50 - Use provided metadata (publication date, location) to resolve date/location
   ambiguities:
```

```
  - For partial dates, infer missing year from the newspaper date.
  - Do not assume event location matches the newspaper location unless explicitly stated.
  - For instance, if the text mentions "the Bank of Smyrna", it should refer to Smyrna, Tennessee, if the context suggests a U.S. location (instead of Smyrna, Turkey, which is unlikely to be discussed in a U.S. newspaper from Tennessee).
- Remember: Articles might reference multiple events in various locations. List them separately.

2. Output rules
   - Match found: If the article describes one or more relevant U.S. banking events, set `is_match` to True and return a list of event objects in the events field. Do not merge multiple events into a single object. Each event must be represented as its own object in the list.

---

Newspaper metadata:

- Name: {scan.newspaper}
- Location: {scan.city}, {scan.state}
- Date published (ISO 8601 formatted date: YYYY-MM-DD): {scan.date}

---

ARTICLE:

```
{article_text}
```

Use the article text above to populate your response.
```

Listing C.2: ***Intermediate dataset.*** *Prompt used to extract structured information about each newspaper article.*

```
You are an expert in historical U.S. banking events. You must analyze the included list of digitized newspaper articles that discuss one or multiple events such as bank runs, bank suspensions, etc., and then classify the overall episode into one of the provided types.

# Output fields.

```

```
Your JSON response must follow this structure:

- `success` (boolean): True if you were able to complete the task successfully
- `episode_type` (string): The type of event, as described below
- `bank_name` (string): The name of the bank. Use the provided bank name unless you detect a typo or other issue.
- `bank_type` (string): The type of bank involved. Must be one of: "national", "state", "trust", "private", or "unknown".
- `city` (string): The city where the bank is located. Use the provided city name unless you detect a typo or similar.
- `notes` (string): Any notes or nuances about your answer that I should be aware of
- `events` (array of objects): A list of events extracted from the article. Each event object must include the following fields:
  - `event_type` (string): The type of event. Must be one of: "run", "suspension", "reopening", "receivership", or "other".
  - `date` (string): An ISO 8601 formatted date (YYYY-MM-DD) string representing when the event took place, or `null` if not provided. You can return partial extractions such as the month by setting unknown fields to zero. For instance, 19091200 for an unknown day in December 1909.
  - `snippet` (string): A direct excerpt from an article that best demonstrates or confirms the event (including any relevant phrases or keywords), or `null` if not provided.

# Types of episode

There are nine possible episode types, based on the chronological order and the causality in which the events took place. You must write the episode type that you think took place in the `episode_type` field:

1. `run_only`: A bank run on this bank took place, and the bank remains open throughout the entire episode (does not suspend or fail)
2. `run_suspension_reopening`: A bank run takes place. As a consequence of the bank run, the bank suspends (either fully by suspending all payments or partially by invoking the 30/60/90 day rule). However, the bank eventually reopens and does not fail.
3. `run_suspension_closure`: A bank run takes place. As a consequence of the bank run, the bank suspends. The bank remains closed permanently and has either a receiver assigned or is taken over by another bank.
4. `run_suspension_unsure`: A bank run takes place. As a consequence of the bank run, the bank suspends. It is unsure if the bank remains closed permanently or if it reopens.
5. `suspension_closure`: A bank suspends. There is no bank run. The bank
```

```
remains closed permanently and has either a receiver assigned or is taken over by another bank.
6. `suspension_reopening`: A bank suspends. There is no bank run. The bank is able to reopen successfully and continues to operate its business.
7. `suspension_run_closure`: A bank suspends. As a consequence of the suspension, depositors run and/or are excited (i.e., they gather outside the bank) in a ill-fated attempt to regain access to their funds. The bank remains closed permanently and has either a receiver assigned or is taken over by another bank.
8. `suspension_run_reopening`: A bank suspends. As a consequence of the suspension, depositors run and/or are excited (i.e., they gather outside the bank) in a ill-fated attempt to regain access to their funds. The bank is able to reopen successfully and continues to operate its business.
9. `other`: Other type of event or sequence. Explain in the `notes` field.


# Guidelines and notes

You must follow these guidelines:

- If you are unable to analyze the articles successfully, or if the article involves bank events in foreign countries outside of the U.S., set `success` to False.
- The article texts may contain significant OCR errors. Correct obvious OCR errors, especially in key fields such as bank names, dates, and locations. Document significant corrections in the notes field.
- **Do not invent or infer details** that are not reasonably supported by the text.
- Please classify the episode and the events based on what happened to the specific bank in question, not to other banks discussed in the articles.
- If the event sequence matches more than one category or is ambiguous, select the most likely option and explain clearly in the `notes` field.
- If possible, be concise when writing in the `notes` field.
- If the text mentions "the Bank of Smyrna", consider that it likely refers to Smyrna, Tennessee, if the context suggests a U.S. location (instead of Smyrna, Turkey, which is unlikely to be discussed in a U.S. newspaper from Tennessee).
- The articles often talk about events in other cities, so you MUST NOT blindly use the newspaper location as the event location. You have made this mistake in the past so please avoid it!
- Use any provided newspaper metadata (e.g., publication date) to help resolve ambiguities, such as when only a month and day are mentioned. For example, if the text says "January 10" without a year, you may derive the year from the
```

```
newspaper date.

Note that historically these events might have been described using various terms, for example:

      - Bank runs: "run on the bank", "heavy withdrawals", "temporary embarrassment", "invocation of the 30 day rule", etc.
      - Bank suspensions: "failure to open", etc.
      - Bank reopenings: "resumption", "resumed operations", etc.
      - Bank receiverships: "assigned a receiver", etc.


# Bank information

- Bank: {bank}
- City: {city}
- State: {state}

# Articles

The articles are listed below:

{articles}
```

Listing C.3: ***Final dataset.*** *Prompt used to process newspaper articles related to a specific bank and distress episode, and produce a description of the overall distress episode, as well as the different events that composed it (suspensions, runs, failures, or reopenings).*

C.2 City Name Validation

In order to identify banks and track them across time—and across different newspaper articles—we first need to validate and standardize their location, as often bank names are only unique within a given city.

We start by validating banks' states and producing their two-digit FIPS code. This is quite straightforward except for former U.S. territories such as "Colorado Territory," "Indian Territory," "Porto Rico," etc. In these cases, we try to assign the location to the successor state (e.g. "Colorado Territory" to "Colorado"). When this is not possible (e.g. "Dakota Territory", which can be assigned to two different states) we try to search all successor states for a match.

Once the states are validated and standardized, we switch to the more complex task

of validating cities[1]. Here we face three problems: first, the U.S. has way more cities and towns than states. Second, towns frequently changed names over time. Third, towns close to large cities could merge into the cities to become suburbs.

We address the first issue by collecting and combining several large datasets of historical U.S. cities:

1. Geographic Names Information System (GNIS) Domestic Names dataset. After dropping locations other than cities and towns—ranging from ranches and towns to national parks and tribal areas—we end up with 209,257 cities and towns.

2. IPUMS NHGIS place point GIS files (Schroeder et al., 2025). These "depict the locations of incorporated, unincorporated, and census-designated places for the entire U.S. from 1900 to 2015." After processing this data and removing certain outliers—such as towns with impossibly long names—we obtain 22,844 cities and towns.

3. Wikipedia articles on U.S. populated areas. We downloaded the entire list of Wikipedia articles, selected those about current and past U.S. populated areas, and compiled a list of those areas including their location and population across time. This yields 25,431 cities and towns.

4. Stanford's Center for Spatial and Textual Analysis (U.S. Census Bureau and Steiner, 2017). This is a curated dataset of 8,848 cities and towns, mostly compiled from the U.S. census and state-level sources.

5. Manually collected datasets. We further rely on the work of Jacob Alperin-Sheriff who manually digitized 20,844 cities from the U.S. decennial census, and of of James Feigenbaum, who digitized a partly overlapping set of 2,442 cities also from the census.

When combining these cities, we perform minimal standardizations on city names, such as replacing "centre" with "center" and "borough" with "boro". This minimizes the possibility of multiple spellings across the different datasets.

Lastly, to deal with city name changes across time as well as conversions into suburbs, we manually create a crosswalk between about 1,000 city names and a chosen canonical representation. Thus, "Wolfboro, NH" becomes "Wolfeboro, NH" and "Morton Park, IL" becomes a suburb of Chicago.

[1]We mostly use only the word "city" but our data includes all populated areas, such as towns, villages, etc.

C.3 Bank Name Validation

Newspapers often mentioned banks with multiple abbreviations and conventions. For instance, the "Enterprise National Bank of Allegheny" could be referred as "The Enterprise National Bank,", "Enterprise National,", "Enterprise NB," "The Enterprise Natl Bank at Allegheny,", and so on.

To address this naming heterogeneity, and standardize bank names across newspaper articles—and when merging with other datasets—we started an ancillary project, `bank-census`, consisting of several well-documented lists of banks, plus a Python package that performs numerous heuristics in order to standardize the bank names obtained from newspapers and match against the valid list of banks.

The six datasets we rely on are:

1. Census of antebellum state banks (Weber, 2006). This contains a manually collected list of all U.S. state banks from 1782 to 1861.

2. Census of national banks between 1863 and 1940 (Correia et al., 2025). This contains the names and main events pertaining all national banks up to 1940.

3. Federal Financial Institutions Examination Council (FFIEC) bank attribute tables. These tables contain the names and main events about all commercial banks between approximately 1940 and today, plus some pre-1940 events for banks that still existed by that date.

4. Census of all banks between 1870 and 1900 (Jaremski and Fishback, 2018). This dataset includes not only state banks but also private banks, not included in the previous sources.

5. Census of all banks regulated by the Department of Financial Services of the State of New York between 1784 and 2025 (New York State Department of Financial Services, 2024).

6. Lastly, a manually collected list of banks. When combined, the previous sources are quite comprehensive but have some gaps. For instance, they exclude state banks that operated exclusively between 1862 and 1869, as well as certain state banks, private banks, and trusts that operated between 1901 and 1940. To address this, we manually verify banks that appear in newspaper articles but not on any of the previous sources, and validate them against contemporaneous records such as Rand McNally, the annual reports of states bank examiners, etc.

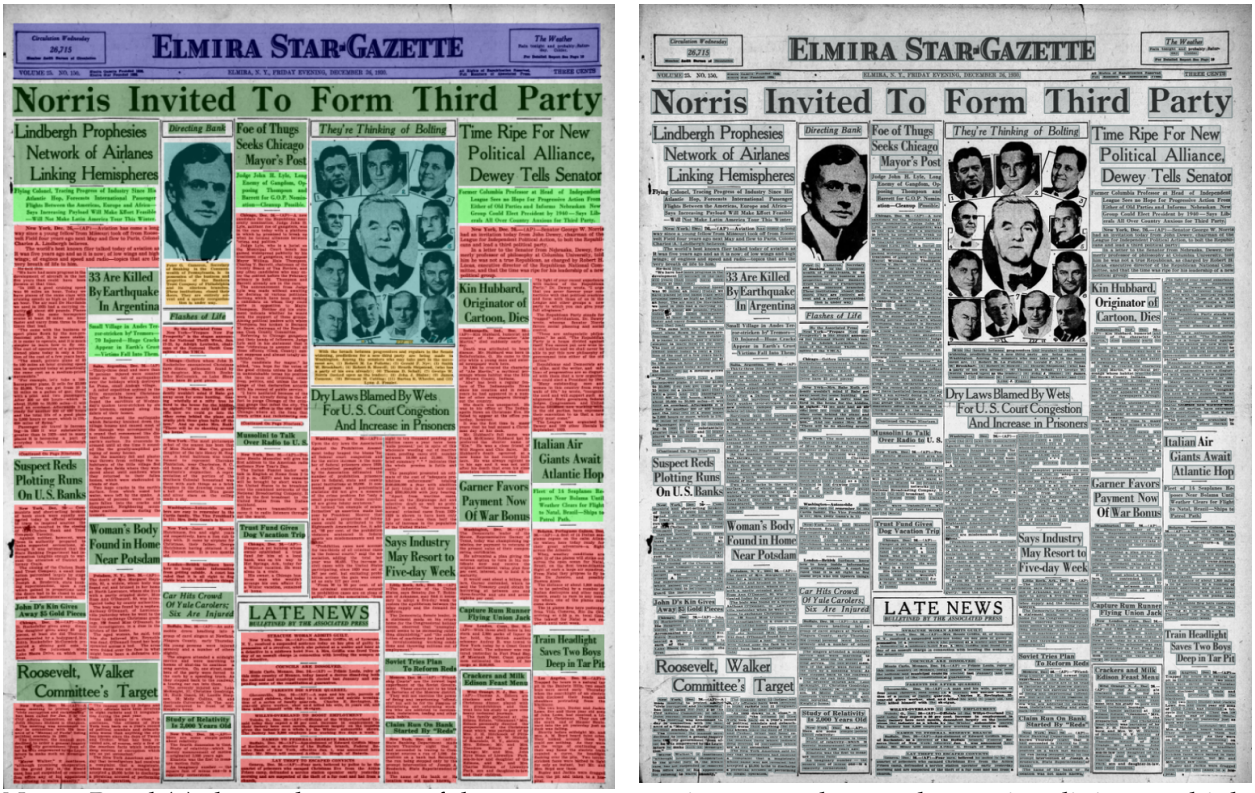
We use these datasets to create a validated list of U.S. banks, which are the main input to our `bank-census` Python package.

This package receives tuples of (state, city, bank), cleans up and standardizes these names, and then matches them against the validated list of banks. If a direct match fails, the package attempts several fallback approaches to find the correct institution. These include replacing common abbreviations, fixing typos, etc. As a large resort, we manually constructed a crosswalk linking about 2,000 names against their standardized versions.

C.4 Illustrative Examples of Newspaper Articles

Figure C.3: *Example of the layout and OCR steps*

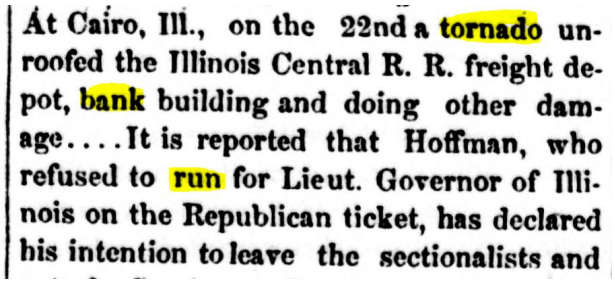
(a) ***Layout:*** *Page segmentation* **(b)** ***OCR:*** *Text extraction*



Notes: Panel (a) shows the output of the page segmentation step, where each page is split into multiple articles, which in turn can be segmented further into headers, main text, images, etc. It was implemented either through code available as part of the *American Stories* project (Dell et al., 2023) or through the *Arcanum* newspaper segmentation product, in case of issues with the first alternative. Panel (b) shows the OCR step, where each we identify the text in each page. It was implemented either via the *Textract* product by AWS or through the OCR tools embedded in *Gemini 2.0* by Google (we used this product as a fallback in case the quality of the OCR obtained by *Textract* was low).

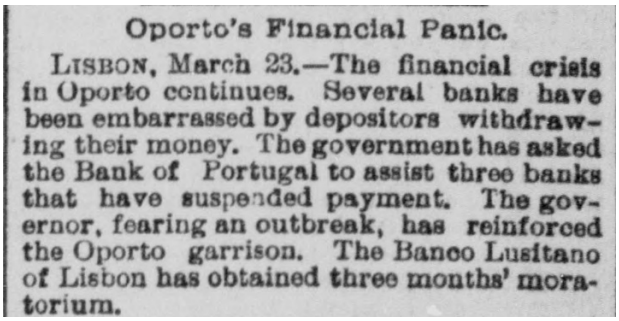
Figure C.4: *Examples of False Positives Flagged by Keywords and Excluded by LLMs*

(a) *Unrelated event*



At Cairo, Ill., on the 22nd a tornado unroofed the Illinois Central R. R. freight depot, bank building and doing other damage....It is reported that Hoffman, who refused to run for Lieut. Governor of Illinois on the Republican ticket, has declared his intention to leave the sectionalists and

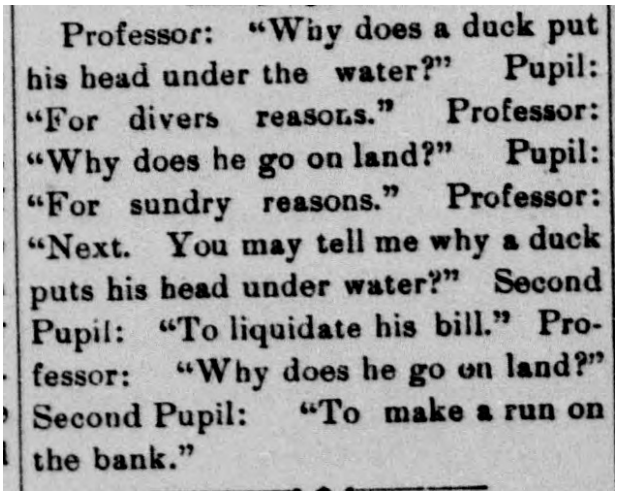
(b) *Foreign bank run*



Oporto's Financial Panic.

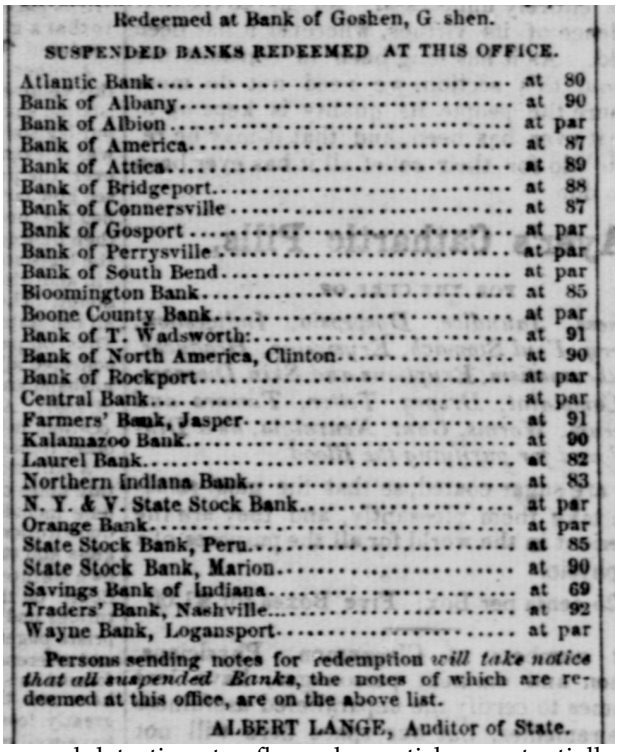
LISBON, March 23.—The financial crisis in Oporto continues. Several banks have been embarrassed by depositors withdrawing their money. The government has asked the Bank of Portugal to assist three banks that have suspended payment. The governor, fearing an outbreak, has reinforced the Oporto garrison. The Banco Lusitano of Lisbon has obtained three months' moratorium.

(c) *Fictional run*



Professor: "Why does a duck put his head under the water?" Pupil: "For divers reasons." Professor: "Why does he go on land?" Pupil: "For sundry reasons." Professor: "Next. You may tell me why a duck puts his head under water?" Second Pupil: "To liquidate his bill." Professor: "Why does he go on land?" Second Pupil: "To make a run on the bank."

(d) *Only tangentially related*



Redeemed at Bank of Goshen, G shen.

SUSPENDED BANKS REDEEMED AT THIS OFFICE.

Atlantic Bank	at	80
Bank of Albany	at	90
Bank of Albion	at	par
Bank of America	at	87
Bank of Attica	at	89
Bank of Bridgeport	at	88
Bank of Connersville	at	87
Bank of Gosport	at	par
Bank of Perrysville	at	par
Bank of South Bend	at	par
Bloomington Bank	at	85
Boone County Bank	at	par
Bank of T. Wadsworth	at	91
Bank of North America, Clinton	at	90
Bank of Rockport	at	par
Central Bank	at	par
Farmers' Bank, Jasper	at	91
Kalamazoo Bank	at	90
Laurel Bank	at	82
Northern Indiana Bank	at	83
N. Y. & V. State Stock Bank	at	par
Orange Bank	at	par
State Stock Bank, Peru	at	85
State Stock Bank, Marion	at	90
Savings Bank of Indiana	at	69
Traders' Bank, Nashville	at	92
Wayne Bank, Logansport	at	par

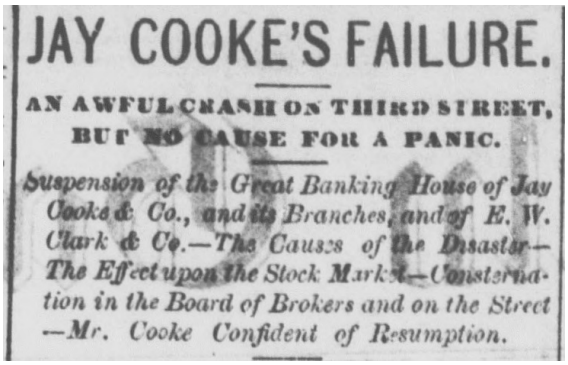
Persons sending notes for redemption *will take notice that all suspended Banks*, the notes of which are redeemed at this office, are on the above list.

ALBERT LANGE, Auditor of State.

Notes: These four example illustrate cases where the keyword detection step flagged an article as potentially relevant for bank distress, but the LLM step detected that the article was, in fact, not relevant.

Figure C.5: *Examples of Articles Discussing Bank Runs or Suspensions*

(a) *Jay Cooke's Failure (1873)*

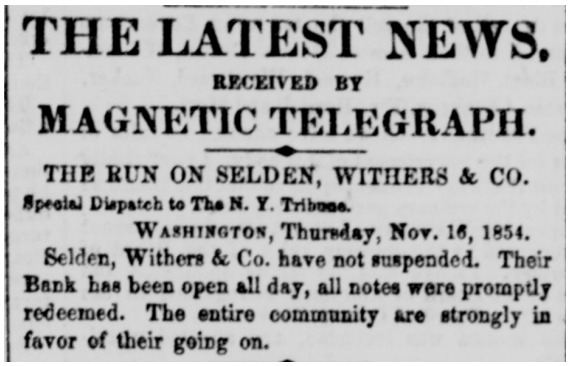


JAY COOKE'S FAILURE.

AN AWFUL CRASH ON THIRD STREET, BUT NO CAUSE FOR A PANIC.

Suspension of the Great Banking House of Jay Cooke & Co., and its Branches, and of E. W. Clark & Co.—The Causes of the Disaster—The Effect upon the Stock Market—Consternation in the Board of Brokers and on the Street—Mr. Cooke Confident of Resumption.

(b) *Run without failure (1854)*



THE LATEST NEWS,

RECEIVED BY

MAGNETIC TELEGRAPH.

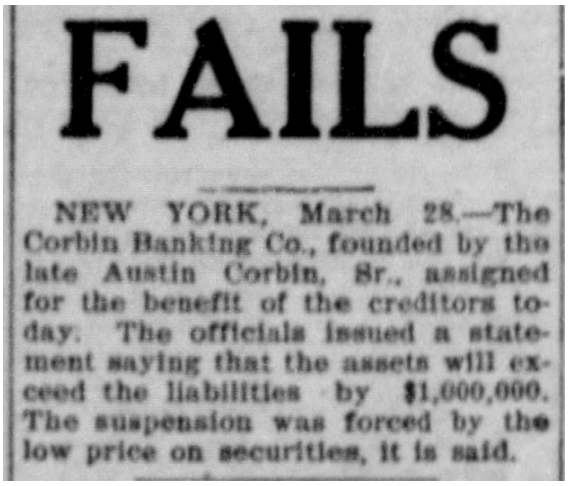
THE RUN ON SELDEN, WITHERS & CO.

Special Dispatch to The N. Y. Tribune.

WASHINGTON, Thursday, Nov. 16, 1854.

Selden, Withers & Co. have not suspended. Their Bank has been open all day, all notes were promptly redeemed. The entire community are strongly in favor of their going on.

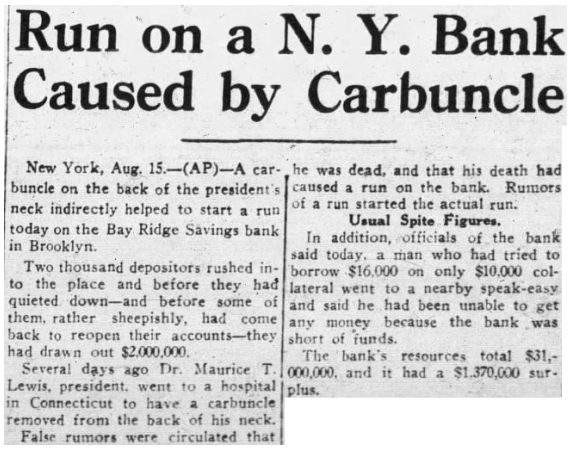
(c) *Bank failure (1907)*



FAILS

NEW YORK, March 28.—The Corbin Banking Co., founded by the late Austin Corbin, Sr., assigned for the benefit of the creditors today. The officials issued a statement saying that the assets will exceed the liabilities by $1,000,000. The suspension was forced by the low price on securities, it is said.

(d) *Sunspot run (1929)*



Run on a N. Y. Bank Caused by Carbuncle

New York, Aug. 15.—(AP)—A carbuncle on the back of the president's neck indirectly helped to start a run today on the Bay Ridge Savings bank in Brooklyn.

Two thousand depositors rushed into the place and before they had quieted down—and before some of them, rather sheepishly, had come back to reopen their accounts—they had drawn out $2,000,000.

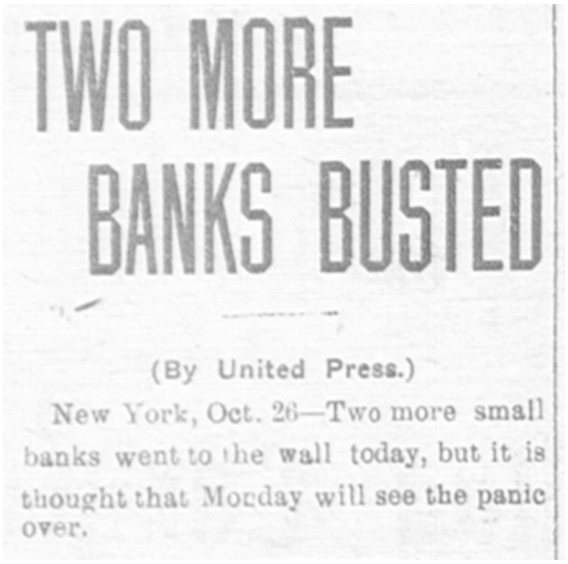
Several days ago Dr. Maurice T. Lewis, president, went to a hospital in Connecticut to have a carbuncle removed from the back of his neck. False rumors were circulated that he was dead, and that his death had caused a run on the bank. Rumors of a run started the actual run.

Usual Spite Figures.

In addition, officials of the bank said today, a man who had tried to borrow $16,000 on only $10,000 collateral went to a nearby speak-easy and said he had been unable to get any money because the bank was short of funds.

The bank's resources total $31,000,000, and it had a $1,370,000 surplus.

(e) *Bank suspensions (1907)*



TWO MORE BANKS BUSTED

(By United Press.)

New York, Oct. 26—Two more small banks went to the wall today, but it is thought that Monday will see the panic over.

(f) *Run followed by failure (1928)*



Cashier Kills Self After Run on Bank

By Untied Press.

MIDDLETON, Del., Dec. 15.—The body of Watson K. Betts, cashier of the People's National bank, which closed yesterday afternoon after a "run," was found in Old Drawers creek today by state troopers.

When the bank was ordered closed yesterday afternoon by Stephen L. Newman, chief bank examiner of the third federal reserve district, no one suspected the cashier of anything except possibly mismanagement of the funds which caused them to be tied up in "rozen assets" on farm loans.

Notes: Examples of bank runs, suspensions, and failures.