Bank Runs With and Without Bank Failure

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Abstract

We study the causes and consequences of bank runs using a novel dataset on bank runs and failures in the United States from 1863 to 1934. Applying natural language processing to historical newspapers, we identify 4,049 runs on individual banks. Runs are considerably more likely in weak banks, but also happen in strong banks, especially in response to negative news about the real economy or the banking system that is not bank-specific. However, runs typically only result in failure for banks with weak fundamentals. Strong banks tend to survive runs through various mechanisms, including interbank cooperation, equity injections, signaling strength, and suspension of convertibility. 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 for bank distress to translate into severe economic consequences.

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1 Introduction

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.

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: What are the determinants of runs? When do bank runs result in bank failure? Can runs trigger the failure of healthy banks and amplify small shocks into large crises? Is the run itself the cause of financial distress or a symptom of deeper fundamental solvency problems in the financial system?

A challenge for understanding the causes and consequences of runs is the absence of systematic micro 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 approach misses the broader universe of runs that do 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 by studying the near-universe of recorded runs in the U.S. banking system from 1863 to 1934. To do this, we create a new database of bank runs by applying natural language processing to historical newspapers. Our novel database identifies 4,049 runs on individual banks in newspaper accounts during 1863-1934. We also capture 14,917 bank suspensions and 12,034 failures. Each event we identify is backed by newspaper accounts and publicly documented at `finhist.com/bank-runs`. Our approach allows us to study bank runs that result in failure, bank runs that result in temporary suspension but not failure, or bank runs that have no further consequences. We merge these data on bank runs with information on bank balance sheets and failures for national, data on macroeconomic conditions, and newly digitized data on local business failures.

We provide three main findings. First, runs are considerably more likely in weak banks, but can also occur in strong banks. Runs on strong banks often occur in response to negative news about the economy that makes depositors jittery. Second, runs typically only result in failure for banks with weak fundamentals. Strong banks survive runs

through various mechanisms that signal solvency. Third, runs with bank failure and bank failures without runs lead to substantially larger local declines in deposits and lending than runs without failure. Taken together, poor fundamentals that erode bank solvency are key for whether runs pass-through into failure and have severe consequences for the broader economy.

The historical U.S. banking system provides an appealing environment to study runs. Our sample covers the numerous panics of the National Banking Era and the Great Depression. 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 1934, making runs much more common in this time period. As a result, this historical laboratory has shaped economists' understanding of bank runs (e.g., Sprague, 1910; Friedman and Schwartz, 1963; Bernanke, 1983; Calomiris and Gorton, 1991; Wicker, 2006), though this work has largely relied on aggregate data.

We start by validating our novel bank run database. Spikes in the rate of bank runs line up closely with existing narrative chronologies of banking crises in the United States (Jalil, 2015; Baron et al., 2021), both at the aggregate and regional level. For national banks, the annual unconditional probability of a run is 0.34%. This number rises to 1.6% during crisis years. Moreover, national bank failures we classify as involving runs involve a 5 percentage point larger deposit outflow right before failure. For surviving banks, runs are strongly correlated with deposit declines in annual data.

With these data, we address three fundamental questions on the role of bank runs in bank failures and financial fragility.

First, what are the determinants of runs? We empirically examine the role of bank fundamentals and negative news about the economy in triggering bank runs. In the data, runs are substantially more likely 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. This finding is consistent with the prediction of theories in which runs occur in response to weak bank fundamentals (e.g., Morris and Shin, 2000; Goldstein and Pauzner, 2005).

At the same time, while less common, even the strongest banks can be subject to runs.

Beyond bank fundamentals, negative news about economic conditions or the banking system also increases the likelihood of runs. Runs are more likely after a downturn in the stock market, a rise in local non-financial business failures, or runs on other banks in the same city. News shocks that are not bank-specific help explain why strong banks can be subject to runs. This evidence is consistent with theories of information-based runs, in which runs arise in response to negative public signals that lead depositors to revise their assessment about the riskiness of deposits (Gorton, 1988; Dang et al., 2017).

Second, when do bank runs result in bank failure? We find that 39% of runs are associated with a bank failure. Thus, there are many runs without bank failure, highlighting the novel insights from our approach. Crucially, 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 an 65% probability of failing. In contrast, runs on *ex ante* strong banks result in failure in 10-25% of cases. Thus, weak bank fundamentals are usually necessary for a run to lead to bank failure. Consistent with this, we observe that banks that survive runs are much stronger on observables than banks that fail following a run.

Runs following negative public signals have contrasting implications for bank failure, depending on the nature of the signal. Runs following runs on other local banks are associated with a lower probability of failure. This suggests news of other runs makes depositors "jittery," leading to a rise in runs on healthy banks that do not result in failure. In contrast, runs following a rise in the local business failure rate are associated with a higher probability of failure, consistent with these runs responding to a rise in bank losses and deteriorating bank solvency.

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. First, full-information models generally do not predict runs without. Instead, this evidence is broadly consistent with information-based 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, weak and strong banks can be separated based on simple public balance sheet metrics, suggesting 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 easily conduct a meaningful financial analysis of bank health. Moreover, the predictability of runs and failures suggests depositors are often sleepy in responding to weak bank fundamentals, but the importance of news shocks suggest salient information can cause depositors to wake up and run.

We also explicitly examine the scope for non-fundamental runs to trigger failure. We define non-fundamental runs as those that are caused by misinformation or depositor confusion and are not related to bank or economic conditions. Using textual analysis, we identify a sample of 40 non-fundamental runs on national banks. This exercise also provides sharper identification by zooming in a set of runs that are relatively free of confounding factors. The probability of failure following a non-fundamental run is 13%, much lower than for the average run. Moreover, we find that these non-fundamental runs trigger failure when they happen to occur in weak or fraudulent banks, reinforcing the key role of poor fundamentals for the pass-through of runs to failure. Non-fundamental runs do not appear to be able to cause failures of otherwise healthy banks, casting doubt on a strong form of the view that liquidity problems alone can trigger severe financial distress.

Strong banks use various mechanisms to survive runs. Newspapers often report that surviving banks accommodate withdrawals and attempt to signal strength to depositors. One such signal is an equity or deposit injection by owners or other investors. Further, 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, often alongside bank examination to signal solvency to depositors. In about 10% of runs, newspapers mention that the local bank clearinghouse is involved by providing liquidity or examination. This evidence is consistent with (Gorton, 1985a), who argues that suspension of convertibility can prevent runs from translating into failure of solvent banks.

Third, what are the consequences of bank runs with and without failure for lending? We next study the bank-level consequences of runs for banks that survive runs. Banks that are subject to runs and survive see a contraction in deposits and loans of about 7.5%. The contraction is persistent, lasting for over four years. To refine the identification, we study the consequences of runs we classify as non-fundamental. Such runs have also have modest negative effects on deposits and lending. Further, bank-level deposit and lending contractions following runs are much stronger for banks with *ex ante* weak fundamentals, while the effects are small and not significant for strong banks. Thus, bank 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 at the regional level: the rate of (i) runs without failure, (ii) failures without runs, and (iii) failures involving runs. We find

that spikes in the local rate of runs *without* failure lead to modest declines in deposits and loans at both the city and state level. In contrast, runs with failure lead to more severe deposit and credit contractions. Interestingly, the consequences of increases in the rate of failures without runs are similar to those of failures with runs.

Taken together, these 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. Our findings temper the view that small shocks can result in large jumps to bad equilibria via runs on demandable debt.

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 new systematic evidence on which banks become subject to bank runs, which shocks trigger runs, which banks fail in runs, how banks survive runs, and the consequences of runs with and without failure for broader credit availability. 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 during the March 2023 banking turmoil. 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. 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.

Further, 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.

Finally, our methodology builds on the narrative approach (e.g., Romer and Romer, 2004). By providing historical classifications of banking crises, the narrative approach has been fruitful for understanding crises (Bordo et al., 2001; Reinhart and Rogoff, 2009; Jordà et al., 2013; Baron et al., 2021). The narrative approach has generally been used in a macroeconomic context with a relatively limited set of events. Our methodology using textual analysis allows us to apply the narrative approach at a scale that would previously

been insurmountable for a small team of researchers. Furthermore, the narrative approach to classifying banking crises involves researcher judgment, leading to some disagreement about which episodes constitute episodes of widespread bank runs (e.g., Jalil, 2015; Baron et al., 2021; Hoon et al., 2025). Our newspaper-based approach provides a systematic approach to resolving these disagreements based on large-scale and consistent analysis of a given corpus of text. It is particularly well-suited to understanding events such as runs when such events are recorded in the text, as it usually does not require judgment to determine whether there is a discussion of a bank run.

Roadmap The next section outlines testable predictions from theories of bank runs. Sections 3 describes the methodology behind the construction of our novel bank runs dataset. Section 4 validates our database and documents the incidence of bank distress in the U.S. from 1863 to 1934. Section 5 studies the empirical determinants of bank runs. Section 6 studies the pass-through of runs to failure. Section 7 examines the consequences of runs for local deposits and lending, and section 8 concludes.

2 Conceptual Framework

To guide our empirical analysis, we outline theories of the causes of bank runs and their implications for whether runs result in bank failure. We then outline the predicted real economic consequences of bank runs with and without failure, contrasting these outcomes to bank failures without runs.

Our emphasis on bank failure as the central outcome is motivated by a long tradition in macro-finance arguing that bank failure is particularly costly for real activity because it disrupts credit intermediation (e.g., Bernanke, 1983). Bank lending is "special" in that it mitigates informational and agency frictions through relationship-based screening and monitoring. When a bank fails, this informational capital and borrower relationships may be destroyed, leading to persistent reductions in credit. As a result, bank failure provides a natural mechanism through which runs can translate into broader real economic costs. Nevertheless, as we discuss below, runs that do not result in failure may still impose economic costs through alternative channels, which we consider separately.

2.1 Causes of Runs and Implications for Bank Failure

One line of theory models runs as resulting from self-fulfilling panics that are not tied to bank or broader economic fundamentals. We refer to these as *non-fundamental runs*.

In the seminal model of Diamond and Dybvig (1983), banks finance illiquid assets with demandable liabilities. This exposes banks to the risk of becoming illiquid if many depositors withdraw simultaneously. Because depositors are served on a first-come-first-served basis, depositors run if they expect others to run, leading to a self-fulfilling panic. A run that renders a bank illiquid will also render it insolvent by leading to a value-destroying fire sale of assets.[1] Non-fundamental runs can therefore even occur in healthy banks, causing failure of these banks.[2] These runs are thus unpredictable jumps to a bad equilibrium that are not necessarily linked to weak fundamentals.[3]

Anecdotal evidence and aggregate data suggest that runs often occur following bad realizations of fundamentals. A second class of models of *fundamental-based panic runs* captures this idea (Morris and Shin, 2000; Goldstein and Pauzner, 2005).[4] In Goldstein and Pauzner (2005), bank fundamentals are stochastic, but agents do not have common knowledge about fundamentals. Instead, each depositor receives a slightly noisy signal of the bank's asset value. This global games set-up can feature a unique equilibrium as a function of fundamentals. A bank run occurs when bank fundamentals fall below a specific threshold. However, importantly, the model generates panic runs, in the sense that, absent the run, the bank would have been solvent and survived.[5] Runs thus amplify bad fundamentals. The empirical prediction is that fundamental-based panic runs should occur in banks with weak fundamentals.[6]

Another set of theories model runs as a response to aggregate public signals that lead depositors to revise their assessment of the riskiness of deposits. We refer to these as *information-based runs*. These aggregate signals are not bank-specific. This class of models assumes that bank assets are opaque and depositors cannot tell apart good and bad banks (Dang et al., 2017). Hence, they run on all banks if a signal is sufficiently bad. For example, depositors might run in response to a signal that a recession is imminent

[1]Value destruction can also occur through liquidation discounts in receivership (Correia et al., 2026) or the loss of deposit franchise value (Drechsler et al., 2023).

[2]This is true up to a point. A very strong bank with a sufficiently high capitalization ratio and a substantial liquid asset buffer will not be brought down by the run, as the depositors can always expect full recovery, so they do not have an incentive to run (see, e.g., Correia et al., 2026).

[3]Many papers explore non-fundamental runs in a Diamond-Dybvig framework (e.g., Peck and Shell, 2003). He and Manela (2016) model the dynamics of information-acquisition in response to rumor-based runs, showing that socially inefficient information acquisition can increase the likelihood of runs. Their model also captures the notion of gradual withdrawals.

[4]See also, Allen and Gale (1998) and Rochet and Vives (2004) for models where runs occur after the realization of poor fundamentals.

[5]In practice, depositors are often sleepy and not attentive to bank fundamentals (e.g., Egan et al., 2025). Therefore, depositors may react slowly to weak fundamentals, leading to runs on weak banks to occur once these banks are already insolvent (Correia et al., 2025).

[6]In Calomiris and Kahn (1991) and Diamond and Rajan (2001), runs are triggered by negative information about bank assets. In these frameworks, demandable deposits are the optimal contract to discipline bankers.

(Gorton, 1988; Calomiris and Gorton, 1991). Such a signal could be a decline in the stock market, a rise in business failures, or runs on other banks. Such runs away from bank debt can occur in response even to small shocks (Gorton, 2012; Gorton and Ordoñez, 2014).[7]

Information-based theories capture the idea that depositors can misinterpret public signals and mistakenly run on healthy banks. For example, depositors might misinterpret a long line at a bank as a signal that the bank is insolvent, even though the line was caused by a liquidity demand shock (Chari and Jagannathan, 1988). Related to this, runs can be driven by herding (Gu, 2011).[8] The bank run in the film *Mary Poppins* is an evocative example. Runs on other banks may lead depositors to revise their belief that their own bank is insolvent and run, an information-based contagion (Chen, 1999). Negative news may also lead depositors to worry that other depositors are more flighty, increasing the propensity to withdraw. Behavioral theories of flawed belief formation can also lead to runs on healthy banks, as captured by the original meaning of the word "panic." Information-based theories predict that panics should occur in response to adverse public signals, leading to runs on weak and strong banks.

Prediction 1. ***Causes of bank runs.*** *Non-fundamentals runs can happen both in banks with weak and strong fundamentals. Fundamental based panics predominantly happen in weak banks. Information-based runs on strong and weak banks occur after negative news that is not necessarily bank-specific.*

What do theories of bank runs predict about bank failure? In standard theories of non-fundamental and fundamental-based panic runs, in equilibrium runs necessarily trigger failure. For example, in Diamond and Dybvig (1983) and Goldstein and Pauzner (2005), the run equilibrium leads to the liquidation of the bank. If the liquidation can be avoided, then there is no run in the first place. Thus, these models predict that, in equilibrium, runs cannot occur without failure.[9]

[7] In recent work by Dang et al. (2020), runs arise when an adverse signal about the collateral banking bank debt leads agents to produce information about bank debt. As a result, there is a regime switch, and bank debt moves from being information-insensitive to information-sensitive. Agents flee bank debt out of fear that others have private information about the value of bank debt.

[8] Gu (2011) writes a model of herding by depositors, where there can be both efficient and inefficient runs. Inefficient runs occur when depositors are misled by past observed withdrawals through an informational cascade.

[9] This statement is based on a version of global games models in which all depositors receive almost the same signal about the state of the world, and which is the most commonly considered version. Note that partial runs that do not result in failure are in principle possible in models such as Goldstein and Pauzner (2005) when the common knowledge assumption is more broadly relaxed and when depositors do not receive the exact same signal, i.e., the noise does not go to zero.

In contrast, information-based theories explicitly allow for runs without failure. Several mechanisms can prevent failure of solvent banks in response to a run, even in the absence of a public lender of last resort. Runs might be managed by accommodating withdrawals or attempting to signal that the bank is solvent, such as through information provision or equity injection. The run in the celebrated film *It's a Wonderful Life* is resolved without failure because George Bailey is able to restore depositor confidence. A run on a healthy bank by uninformed depositors can also be managed by interbank cooperation. An interbank loan can cover temporary liquidity shortfall. In the National Banking Era, bank clearinghouses would regularly inspect member banks and provide liquidity in response to runs (Gorton, 1985b). Heavy runs can be resolved by suspension of convertibility, whereby banks refuse to convert deposits into currency for a time. Gorton (1985a) models suspension of convertibility as a costly way for a solvent bank to signal its solvency and avoid an inefficient liquidation. If these mechanisms are empirically relevant, then they should imply that even if runs on solvent banks do occur, they should rarely lead to bank failures.[10]

Prediction 2. ***Bank runs and failures.*** *Non-fundamental and fundamental-based runs necessarily result in bank failure. Information-based runs predict strong banks can survive through various mechanisms, including interbank cooperation, suspension, and examination.*

2.2 Broader Economic Consequences of Runs and Failures

Our analysis speaks to two broad conceptual views about the consequences of runs for the banking system and the real economy. One view is that runs are key discontinuous turning points whereby small shocks translate into large economic costs through bank failures and credit contraction. Theories of non-fundamental runs, fundamental-based panic runs, and information-based runs all share this prediction (Diamond and Dybvig, 1983; Goldstein and Pauzner, 2005; Gorton, 2012; Gertler and Kiyotaki, 2015).[11] This view also plays a key role in prominent accounts of the Great Depression and Great Recession (Friedman and Schwartz, 1963; Bernanke, 2018).

Another view is that runs themselves are not the root cause of severe downturns, but are instead primarily a reflection of deeper fundamental solvency problems (Gennaioli

[10]Note that information-based runs where agents make mistakes can be resolved with suspension, but they still occur in equilibrium. However, in full-information models, such as classic models of non-fundamental runs, suspension of convertibility would rule out inefficient runs on solvent banks in the first place.

[11]For instance, Gorton (2012) argues that even runs that lead to suspension but not failure are highly disruptive to local business activity.

and Shleifer, 2018; Baron et al., 2021). Solvency problems are the cause of severe economic contraction, as in models of the bank lending channel (Holmstrom and Tirole, 1997; Gertler and Kiyotaki, 2010). Bank capital is the key state variable capturing the ability of the banking system to intermediate funds. If runs often arise in response to these fundamental weaknesses, they may be the trigger that results in inevitable bank failures and economic costs, but not their root cause. In this view, avoiding runs would not prevent the costs of poor fundamentals. At the same time, even if runs are not the root cause of banking sector distress, runs may be an important amplification mechanism for bad fundamentals, leading to worse outcomes than if the run were averted (e.g., Goldstein and Pauzner, 2005; Gertler and Kiyotaki, 2015).

While these two views are challenging to fully distinguish, they entail different implications. On the one hand, if runs themselves are key, then runs should typically trigger severe outcomes. On the other hand, if runs are the recognition of bad fundamentals, then runs should be especially costly when fundamentals are weak and when they lead to failure. Runs on strong banks that do not lead to failure should not be associated with the same economic costs. Moreover, the bank failures without runs, which can occur if banks are deemed insolvent and closed by supervisors or bank owners before a run, should also be associated with severe consequences.

Finally, even absent outright bank failure, runs may have adverse real effects by reducing the quantity and increasing the cost of bank funding, thereby increasing the cost of credit intermediation. Theoretical models of the *bank lending channel* capture the idea that financing constraints among borrowers and banks imply real effects of shocks to bank funding or capital (Holmstrom and Tirole, 1997).[12] Again, in cases where banks survive a run, bank-lending channel models predict that the cost of these runs is higher in weaker, less well-capitalized banks. Our analysis will thus compare runs with and without failure in weak and strong banks to test this idea.

Prediction 3. ***Real consequences of runs and failures.*** *Runs should lead to more severe outcomes if they occur in banks with weak fundamentals and trigger bank failure. Moreover, failures without runs should be associated with comparably adverse outcomes for the local economy.*

[12] A large empirical literature finds evidence for this channel (e.g., Peek and Rosengren, 2000; Khwaja and Mian, 2008; Ivashina and Scharfstein, 2010; Chodorow-Reich, 2014; Huber, 2018).

3 Data

3.1 Novel Bank Distress Events Database

Concepts and Definitions We construct a novel and comprehensive dataset of bank run events recorded in newspapers for all U.S. banks between 1863 and 1934. 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.

We also collect newspaper mentions of other key bank events: suspensions, reopenings, and failures. 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. 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.[13] 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.[14] Figure B.2 shows the number of articles used in our final analysis across time and source.

[13] *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.

[14] 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 B.1).

Methodology We produce our dataset of bank distress events in two stages. The procedure is summarized in Figure B.3. 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 B.4, 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 B.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.[15] 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 a bank run or other form of 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 B.6 for some examples).

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 B.3 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 B.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

[15] See Listing B.1 for the LLM prompt used and Figure B.5 for some examples of articles filtered out.

that is robust to typos and variations on how bank names are written.[16] This allows us to match 66% of all bank names between 1863 and 1934, and up to 90% if we focus only on national banks for 1863-1935.[17]

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.[18]

Episode Types Our bank distress episodes can be interpreted as a self-consistent list of events that affected a specific bank. As mentioned above, we classify bank runs, suspensions, and failures. We then further classify bank distress episodes finer following categories based on their internal dynamics. First, we can thus study episodes with runs but no failure, distinguishing between those resolved with and without suspension:

- *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.
- *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.

Next, we can consider runs with failure:

- *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.

Further, we also consider episodes with failure but without a run:

- *Failure without run.* A bank suspends. There is no recorded bank run. The bank remains closed permanently and has either a receiver assigned or is taken over by another bank.

[16] See Appendix B.3 for additional details.

[17] 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.

[18] Due to cost and current limitations in LLMs, we only include up to 25 articles for each bank episode queried.

Note that by definition a bank must suspend before failing. 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).

Measurement Issues We briefly note three 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. Third, during crises, newspapers will sometimes speak more generally about several banks in an area being subject to runs or suspension, without explicitly listing all banks. Thus, we may underestimate the number of bank-specific episodes during crises.

3.2 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.[19] 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).

[19]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).

To capture for local defaults that can trigger bank asset losses, we create novel a state-level dataset of quarterly non-financial business failures covering 1886-1935 by digitizing various issues of *Bradstreet's*. To obtain a business failure rate, we scale non-financial business failures by the number of manufacturing establishments from the census. 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).

4 Bank Runs in the US, 1863-1934

This section provides an initial look at the incidence of bank runs, suspensions, and failures in the US from 1863 to 1934. In the process, we validate the quality of our newly constructed database, a key step to ensure the reliability of our findings.

4.1 Descriptive Statistics on Bank Distress Episodes

Panel (a) of Table 1 reports the raw counts of bank runs, failures and suspensions identified in our new database for all bank types. Figure 1 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.

During the 1863-1934 period, our dataset contains 4,049 bank run episodes. The majority of runs do not involve failure. We find 2,155 runs without failure and 1,887 runs with failure. We also find 14,917 episodes involving a suspension, and 12,034 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.

Panel (b) in Table 1 shows the unconditional probability of bank distress episodes in 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. For national banks, we also have clear records that determine whether a bank failed, as the OCC recorded all national bank receiverships.[20] A national bank's annual unconditional probability of failing between 1864 and 1934 is 0.72%, while the unconditional probability of being

[20]There is no census on the universe of non-national banks. Moreover, there is no systematic information on failures of state banks or trusts. Therefore, much of our analysis relies on the merged sample of national banks.

Table 1: ***Bank Runs, Failures, and Suspensions in Newspapers, 1863-1934***

Panel A: Total number of events, all bank types

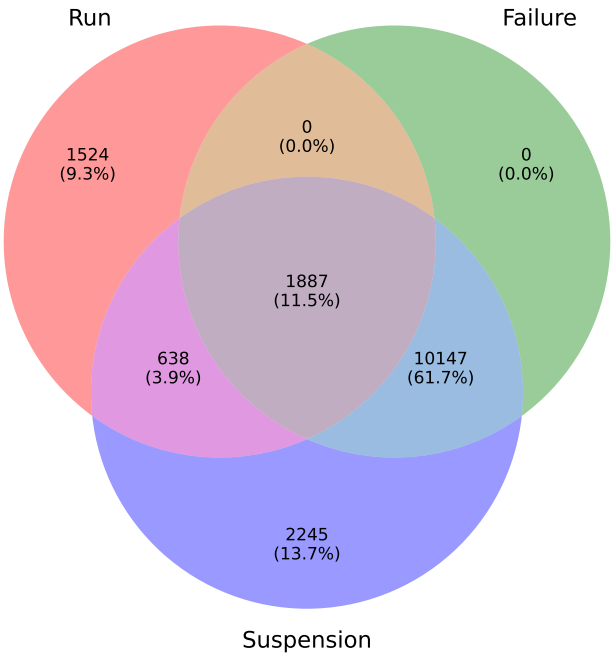
Sample	Bank run				Failure	Suspension
	All	Run w/o suspension	Run with sus. + reopen.	Run with failure		
All	4049	1524	631	1887	12034	15216
No crisis	2121	844	230	1042	7698	8852
Banking crisis	1928	680	401	845	4364	6392
1863-1913 (NB Era)	2235	1078	341	810	5191	6561
1914-1918 (Early Fed)	667	203	86	378	2751	3149
1929-March 6, 1933	1073	218	191	663	3022	3756
After March 6, 1933	74	25	13	36	1070	1750

Panel B: Number of events as a share of total number of banks, national nanks

Sample	Bank run				Failure	Suspension
	All	Run w/o suspension	Run with sus. + reopen.	Run with failure		
All	.367	.159	.0597	.15	.72	.973
No crisis	.209	.0936	.0225	.0937	.431	.528
Banking crisis	1.54	.648	.329	.569	2.87	4.25
1863-1913 (NB Era)	.38	.182	.0712	.127	.308	.533
1914-1918 (Early Fed)	.173	.0732	.0118	.0876	.614	.645
1929-March 6, 1933	1.18	.337	.126	.728	3.9	4.13
After March 6, 1933	.262	.0388	.0581	.174	6.15	9.1

Notes: Panel (a) reports the counts of all runs, suspensions, and failures 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. Panel (b) reports the average annual rate of runs, suspensions, and failures for national banks, defined as the number of distress events indicated in the table header divided by the number of national banks in the same year. For this sample, 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).
In both panels, we distinguish between runs without suspension ("run only"), runs with suspension and reopening, and runs with failure. We also 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 as identified in Baron et al. (2021).

Figure 1: *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 for all bank types. By definition, failure requires suspension, so there are no observations with failure without suspension.

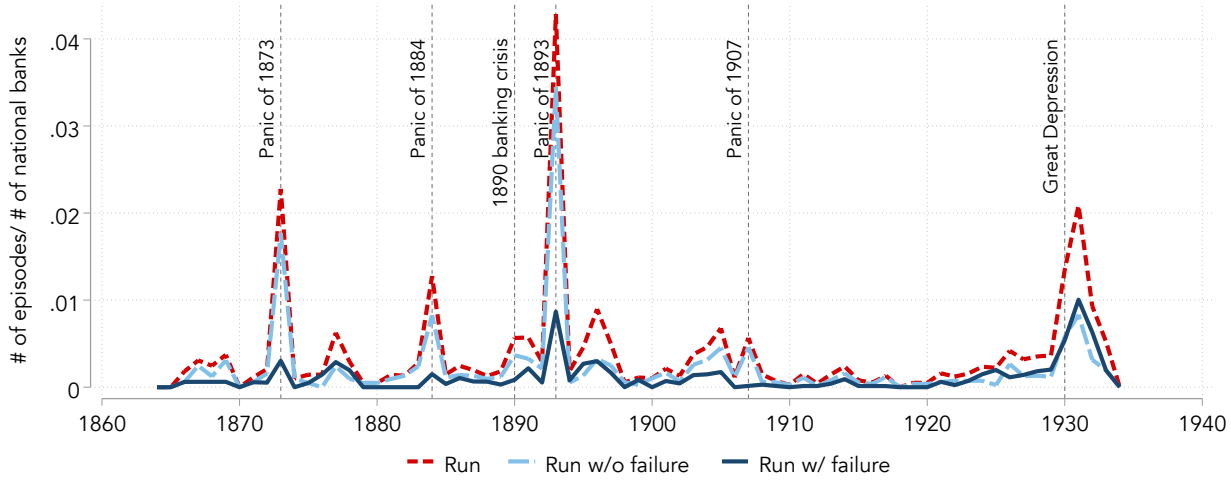
subject to a run is 0.37%. Over the same time, national banks also face a 0.22% probability of being subject to a bank run without failing. About one-fourth of runs without failure involve suspension.

The fact that we observe many runs *without* failure is somewhat surprising and constitutes the first insight from 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 theories of information-based 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. In these theories, a run does not lead to failure if the bank is revealed to be solvent after an examination triggered by the run, possibly in conjunction with suspension. Runs without failure are also potentially consistent with behavioral panics. We study the determinants for whether a run results in failure and how banks manage to survive runs in detail below.

4.2 Bank Runs During and Outside of Narrative Banking Crises

We next study the rate of runs in the time series. Figure 2 plots the number of runs as a fraction of the total number of banks in each year.[21] We again focus on national banks. The rate of runs spike during the major crises years: 1873, 1884, 1893, 1907 (to a lesser extent), and the Great Depression. This incidence of runs confirms prominent narratives of crises in the pre-FDIC era (e.g., Calomiris and Gorton, 1991; Wicker, 1996, 2006).

Figure 2: ***Bank Runs With and Without Failure, National Banks, 1863-1934***



Notes: This figure plots the ratio of the number of national banks subject to a run over the total number of national banks in each year. The number of national banks each year is from Correia et al. (2025). The figure also separates runs into runs without failure and runs with failure.

Figure 2 also distinguishes between bank runs with and without failure. Runs without failure are especially pronounced during major banking crises, especially the "panics" of the national banking era. For example, the Panic of 1893 featured a particularly large number of runs without failure (but with temporary suspensions), as noted by previous work (e.g., Carlson, 2005).

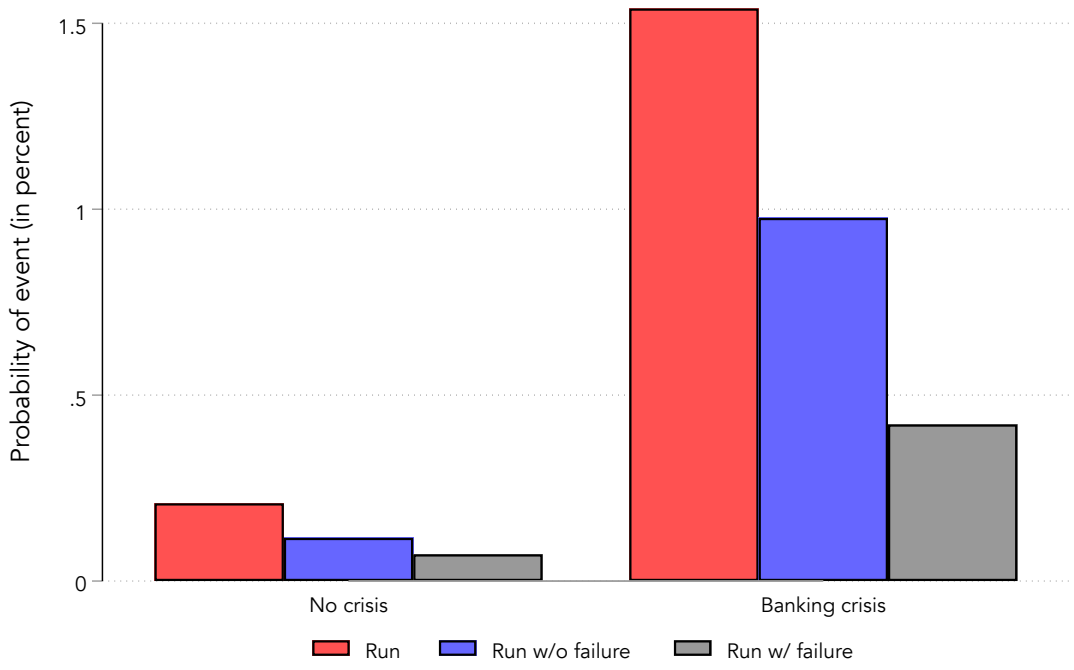
Appendix Figure A.1 plots the rate of bank failures with and without runs. Most failures do not involve narrative discussions of runs, so the "Failure without run" line usually lies above the "Failure with run" line. Failures with runs spiked during the Panic of 1893 and the Great Depression. Failures without runs were elevated during the 1890s and 1920s agricultural downturn.

[21] Appendix Figure A.1 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, such as 1893 and the Great Depression. We 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.

Appendix Figure A.2 plots the rate of bank runs 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.

In the time series, runs and other bank distress episodes appear much more likely during major banking crises. Figure 3 confirms this visual impression by plotting the rate of runs during and outside of banking crisis years. Crisis years are based on the narrative chronology of Baron et al. (2021).[22] The probability of a run increases by roughly a factor of eight during banking crisis years compared to other years. Further, Panel (b) in Table 1 shows a more detailed breakdown of the probability of various distress episodes separating by years with and without a banking crisis. For instance, bank runs that trigger a suspension but do not result in failure become 13 times more likely during crises.

Figure 3: ***Probability of Bank Runs With and Without Failure for National Banks During and Outside of Banking Crises***



Notes: The figure plots the probability of bank runs, runs without failure, and runs with failure during and outside of years identified as banking crises in Baron et al. (2021). The sample is all national banks during 1863-1934. Figure A.3 plots the probability of runs, suspensions, and failures during and outside of crises.

[22]Figure A.3 plots the probability of runs, failures, and suspensions during and outside of banking crisis years. Figure A.4 shows the breakdown by more detailed episode types.

We next confirm in a regression framework that bank runs and other distress events are substantially more likely in years and U.S. states that have been classified as having a banking crisis/panic by narrative chronologies of crises. Table 2 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,[23] while Baron et al. (2021) provide years of the onset of banking crises and the starting month of major banking panics. With this narrative information, we estimate the following regression at the state-month level:

$$\begin{aligned}\text{Num bank distress events}_{st} = \beta_0 &+ \beta_1 \times \text{Major banking crisis}_t \\ &+ \beta_2 \times \text{Major panic month}_t \\ &+ \beta_3 \times \text{Regional banking panic}_{st} + \epsilon_{st}.\end{aligned} \tag{1}$$

The dependent variable is the number of runs, suspensions, and failures at the state-month level. Major banking crisis$_t$ is a dummy that takes a value of one in years of major banking crises, and Major panic month$_t$ is a dummy that is one in months of major banking panics, with the timing of both crises and panics are defined as in Baron et al. (2021).[24] Regional 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.

Our database of bank distress events correlates strongly with existing narrative chronologies of banking crises in U.S. history. On average, there are 0.4 bank runs events per state per month. During years with a banking crisis, the number of runs in a state-month increases by 0.49 on average. During panic months, the number of events increases by another 2.1. During months of non-major regional banking crises identified by Jalil (2015), the number of runs increases by 6. Bank suspensions and failures display a similar pattern. Further, in Table A.1, we include dummies for individual regional crises identified by Jalil (2015) in the regression. Individual crises see considerable increases in the number of runs and failures. For instance, the number of runs increases by 22 during the Florida "Fruit Fly Panic" in July 1929 (Carlson et al., 2011). Overall, we take this as an indication that our database of runs lines up quantitatively with existing qualitative narrative chronologies of banking crises aggregate and regional level.

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

[24] Baron et al. (2021) define panics as episodes of severe and sudden withdrawals of funding by bank creditors from a significant part of the banking system.

Table 2: ***Bank Runs, Suspensions and Failures Correlate with Narrative Banking Crisis Classifications***

Dependent variable	Run	Failure	Suspension
	(1)	(2)	(3)
Major banking crisis year	0.49***	0.68***	1.36***
	(0.061)	(0.16)	(0.19)
Major banking panic month	2.11**	-0.60***	2.04**
	(0.94)	(0.19)	(0.82)
Regional banking panic	6.10***	2.78***	7.49***
	(1.10)	(0.39)	(1.46)
N	11318	11318	11318
Mean dep. var.	0.40	0.86	1.09

Notes: This table reports estimates of Equation (1) using a monthly state-level panel with the number of distress events as the outcome variable. Major banking crises and major banking crises panic month are taken from Baron et al. (2021) and regional banking crises are from Jalil (2015). Table A.1 presents estimates separately including a dummy for each regional crisis. The sample period is 1863-1934. Standard errors clustered at the state level. *,**, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

4.3 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. The aim of this exercise is to test how information newspapers are about a bank distress event where we know the "truth." 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 correlation between the true failure rate and the failure rate based on newspapers in annual data 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 illustrates the same comparison 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 during the March 1933 Bank Holiday only had a receiver formally appointed

later in 1933 or 1934. Overall, this indicates that newspapers are highly informative about important bank distress events.

Second, Figure A.5c plots the probability of a run or failure 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 5 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.

The previous exercise focuses on deposit outflows conditional on bank failure. As a final exercise, Figure A.5e plots the probability of a bank distress episode as a function of annual deposit growth for surviving banks. Runs, runs without failure, and suspensions without failure are all significantly more common for banks in the bottom 1% of the deposit growth distribution. Thus, our classification of runs correlates with statistical evidence of deposit outflows. At the same time, banks in the bottom percentile of the deposit growth distribution only have a 5% probability of some sort of distress event. The events we identify are rarer than merely looking at banks with large deposit outflows, which may be driven by a variety of benign factors.

5 Determinants of Bank Runs

What are the characteristics of banks subject to runs? Which shocks trigger runs? Are the determinants of runs the same as the determinants of bank failure? Guided by the predictions of the theories discussed in Section 2, this section presents evidence on the determinants of bank runs.

5.1 Empirical Framework

We assess the likelihood of a bank run as a function of bank-specific and broader economic conditions. On the one hand, non-fundamental runs should not be predictable. On the other hand, fundamental-based runs should be more likely in weak banks, while information-based runs should be more likely after adverse public signals about the state of the banking sector or the macroeconomy. We thus examine the ability of various sets of variables to capture an elevated risk of runs. We also compare the determinants of bank runs to those of bank failure.

Our goal is to describe the relationship between the likelihood of runs as a function of bank-specific fundamentals and public signals that may trigger runs. To do this, we estimate predictive regressions of the following form:

$$\text{Run}_{bt+1} = \beta_0 + X_{bt}^{Bank}\beta + X_t^{Macro}\gamma + X_{bt}^{Local}\delta + \epsilon_{bt+1}, \tag{2}$$

where Run_{bt+1} is an indicator variable for whether bank b is subject to a bank run within the next year. In addition to examining bank runs, we also present results for several other outcomes: bank runs that do not result in failure, runs that result in failure, and all failures. The model allows us to test whether runs are predictable, and whether factors that imply a higher probability of a run are similar to those indicating a higher risk of failure. We use the sample of all national banks from 1863 to 1934, as this analysis requires data on bank-level fundamentals. We compute Driscoll and Kraay (1998) standard errors with a bandwidth of three years to allow for residual correlation within and across banks in proximate years.

On the right-hand side, we include a range of fundamental bank balance-sheet metrics in X_{bt}^{Bank} 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 deposits-to-assets as a measure of leverage.

Third, in X_{bt}^{Bank} we also include a measure of noncore funding. Noncore funding is defined as the ratio of non-deposit and non-equity funding to total assets. 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 troubled banks suffering losses (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.

Fourth, we include the liquid assets ratio as a proxy of both a bank's available liquid funds to accommodate withdrawals but also as a proxy of the riskiness of a bank's investment mix. Finally, we include recent asset growth. Troubled banks might contract shortly before failure, and recent asset growth thus contains potential information about the future likelihood of failure.

We also examine whether adverse public signals that are salient to depositors imply an increase in the likelihood of a run. In X_t^{Macro}, we include aggregate information that is not specific to bank b that might lead depositors to revise their probability that banks are troubled. Specifically, we include the following time series variables: annual total return on the stock market, real GDP growth, the aggregate national bank failure rate, the aggregate rate of runs on national banks, and the aggregate non-financial business failure rate. In X_{bt}^{Local}, we include local public signals: an indicator for whether there is a run on another bank in the same city and the state-level non-financial business failure rate. All variables are measured as of year t. For example, the stock market return used to predict a run in year $t+1$ is measured as the return from December $t-1$ to December of t.

In addition to the estimated coefficients, we are interested in the extent to which bank-specific fundamentals and economic conditions can predict bank runs and other bank distress episodes. To assess predictability, we calculate the area under the receiver-operating characteristic curve (AUC) for various predictive models. The receiver-operating characteristic (ROC) curve traces the true-positive rate against the false-positive rate across classification thresholds. 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.

5.2 Determinants of Runs

Table 3 presents the results from predicting bank runs as a function of bank fundamentals, macro conditions, and local economic conditions. Column 1 uses only bank fundamentals. It shows that banks with low solvency (proxied by surplus-to-equity) and a high reliance on noncore funding are more likely to experience a run. The interaction between the solvency and noncore funding measures is also predictive of runs. Further, banks with a low share of liquid assets are more likely to be subject to a run. Higher deposits to assets, indicating of higher leverage, is also positively related to runs. These patterns are consistent with the notion that runs are more likely in banks that are closer to insolvency

and less liquid, consistent with theories of fundamental-based runs.

Column 2 in Table 3 focuses on the information content of adverse public signals about the economy and the banking system that are not bank-specific. We find that runs are more likely following years with low stock returns. They are also more likely when business failures are high, although the effect is not statistically significant.

Column 3 focuses on the predictive content of local economic conditions. Runs are significantly more likely following a run on another bank in the same city. The likelihood of a run is also elevated when the state-level business failure rate is higher. These findings are consistent with information-based runs, whereby agents observing adverse news about the economy or banking system revise their probability that other local banks are troubled, increasing the likelihood of runs on other banks.

5.3 Predictability of Runs With and Without Failure

Table 4 studies how well the three sets of variables can classify bank runs and other bank distress episodes based on the AUC metric. Panel A focuses on the predictability of bank runs. Panel A, column 1 shows that bank runs are only moderately predictable based on bank fundamentals, with an AUC of 0.67.

Table 4 column 2 includes year fixed effects in the predictive regression. This specification asks what is the highest AUC that can be obtained from annual time series variation. Including year fixed effects substantially increases the AUC for predicting runs to over 0.82. Thus, time series variation is an important source of variation in runs. This is consistent with runs clustering in particular "panic" years.

In columns 3-5, we attempt to "interpret" the year fixed effects by including the proxies of economic condition. Adding information on local conditions substantially increases the AUC for bank runs, moving the AUC closer to the specification with year fixed effects. The AUC of 0.75 in column 5 indicates that runs are reasonably, though not extremely, predictable based on bank-level and aggregate information.

We next compare the predictability of bank runs with and without failure (Table 4 panels B and C). We also compare the predictability of runs to the predictability of bank failures (panel D). Column 1 in Table 4 reveals that bank fundamentals are much more strongly related to bank runs *with* failure compared to bank runs without failure. Runs without failure are essentially unpredictable based on bank fundamentals, with an AUC of only 58%. In contrast, bank failures are tightly linked to bank fundamentals, consistent with the findings in Correia et al. (2025).

Column (2) shows that including year fixed effects substantially increases the AUC

Table 3: ***Predictability of Bank Runs Based on Bank Fundamentals and Economic Conditions***

Dependent variable	Run in $t+1$			
	(1)	(2)	(3)	(4)
Bank fundamentals:				
Surplus/Equity	-0.26**			-0.46**
	(0.12)			(0.17)
Noncore funding	7.11***			6.23***
	(1.96)			(2.01)
Surplus/Equity × Noncore funding	-5.35**			-5.55**
	(2.67)			(2.56)
Liquid Assets/Assets	-0.49**			-0.57*
	(0.23)			(0.32)
Deposits/Assets	0.68*			0.40
	(0.37)			(0.31)
Asset Growth (3 years)	-0.13			-0.02
	(0.12)			(0.08)
Macro conditions:				
NB failure rate		-1.91		-1.63
		(3.61)		(3.98)
NB run rate		8.78		0.62
		(15.39)		(14.87)
Business failure rate		14.62		15.99
		(12.26)		(13.05)
Real GDP growth		0.65		0.26
		(0.82)		(0.71)
Stock market return		-0.58**		-0.56**
		(0.25)		(0.23)
Local conditions:				
Run on other bank in same city			2.24***	2.17***
			(0.71)	(0.72)
Local business failure rate			10.95***	1.60
			(3.78)	(5.39)
N	283417	274721	271156	237690
Mean dep. var	.3	.33	.33	.33

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.

for predicting runs *without* failure. The relative increase is more modest for predicting runs *with* failure. This suggests that time series variation is especially important for understanding runs *without* failure, while bank-specific fundamentals are more important for classifying runs with failure. As a result, the inclusion of variables capturing macro and local conditions lead to a substantial increase in the AUC for bank runs without failure. However, it leads to more modest improvement for predicting runs with failures.

Overall, the evidence indicates that, to understand bank runs, both bank fundamentals and adverse local and macro news play an important role. For runs without failure, adverse macro news is substantially more important than bank-specific information for explaining the variation. This is in line with banking panics occurring after bad macro news, leading to runs even on healthy banks. While balance sheet metrics contain substantial information for distinguishing strong and weak banks, confused depositors do not fully incorporate this information. On the other hand, bank fundamentals are much more important for understanding bank runs with failure, and bank failures more broadly. Bank failures, including those with runs, tend to occur in banks with the weakest balance sheets, consistent with the evidence in Correia et al. (2025). Thus, fundamentals-based theories are promising for explaining bank runs and failures, while information-based theories are important for explaining runs without failure.

Table 4: ***AUC Metric for Predictability of Bank Runs and Bank Failures***

Prediction horizon h	1 year					
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Bank run						
AUC	0.674	0.822	0.725	0.747	0.754	0.824
Panel B: Bank run without failure						
AUC	0.575	0.816	0.670	0.673	0.706	0.816
Panel C: Bank failure with run						
AUC	0.813	0.876	0.848	0.858	0.862	0.887
Panel D: Bank failure						
AUC	0.868	0.896	0.892	0.890	0.896	0.906
Specification details						
Bank fundamentals	✓	✓	✓	✓	✓	✓
Macro conditions			✓		✓	
Local conditions				✓	✓	✓
Year FE		✓				✓

Notes: This table reports the area under the receiver operating characteristic curve (AUC) across different outcome variables (rows) and specifications (columns). The corresponding regression coefficients underlying the models are reported in Table A.3 (for Panel A), Table A.4 (for Panel B), Table A.5 (for Panel C), and Table A.6 (for Panel D).

6 Bank Runs and Bank Failure

As we argued in Section 2, a key channel through which runs can lead to adverse real effects is via bank failures. We next investigate the relation of bank runs and bank failures in more detail. 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 banks with weak fundamentals? The previous section showed that runs are more likely in banks with weak fundamentals. Yet even strong banks can be subject to runs, especially in response to adverse public signals. In this section, we show that 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.

6.1 Bank Runs and Failure across Weak and Strong Banks

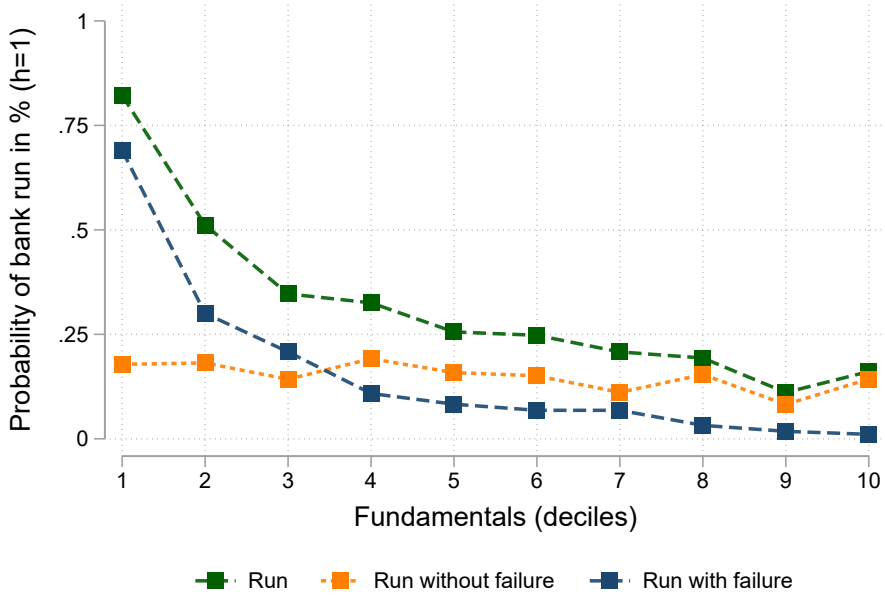
Summarizing Fundamentals We construct a simple bank-level measure of fundamentals, Fundamentals_{bt}, based on the regression of bank failure on bank fundamentals (i.e., in column (1) of Table 4 with only bank fundamentals, reported in column (1) of Table A.5). The idea is to summarize fundamentals that 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 $t+1$ based on bank fundamentals.[25]

Fundamentals and Bank Runs With and Without Failure Figure 4 provides a simple visualization of the relationship between bank fundamentals and the likelihood of a run, a run with failure, and a run without failure. It shows the conditional probability of a bank run 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 nearly 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. Moreover, the relatively low likelihood of a run for the weakest banks is consistent with the modest predictability of runs shown above.

Figure 4 also 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

[25] Before proceeding, we note that the results are similar when defining this measure based on a regression predicting bank runs rather than failures.

Figure 4: ***Probability of Bank Runs by Bank Fundamentals***



Notes: This figure plots the probability of a bank run, bank runs that do not result in failure, and bank runs that do result in failure across deciles of a proxy of bank-specific fundamentals (see text for definition).

to fundamentals (see the yellow line). These runs 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). Runs with failure are almost exclusively concentrated in banks in the lowest decile of fundamentals. Moreover, a bank that is in or above the 7th decile of the fundamentals distribution will essentially never be subject to a run and fail. 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.

Pass-through of Bank Runs to Bank Failure We formally study the importance of bank fundamentals for whether a bank can withstand a run by estimating the following specification for the pass-through of a bank run into failure:

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

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. 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.

Table 5: ***Pass-Through of Runs to Failure: The Role of Bank-Specific Fundamentals***

Dependent variable	Failure in t+1			
	(1)	(2)	(3)	(4)
Run	0.39***	0.26***	0.44***	0.38***
	(0.053)	(0.042)	(0.053)	(0.058)
Fundamentals		-3.48***		
		(0.75)		
Fundamentals × Run		-12.8***		
		(1.92)		
Strong Fundamentals			-0.0100**	-0.0060**
			(0.0040)	(0.0028)
Strong Fundamentals × Run			-0.33***	-0.32***
			(0.047)	(0.047)
Observations	265717	265717	265717	71682
Mean dep. var.	0.0085	0.0085	0.0085	0.0051
Sample				Large Banks

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.

Table 6 presents the results from estimating Equation (3) for the sample of national banks from 1863 to 1934. Column 1 shows that 37% of bank runs are associated with bank failure. Thus, runs often result in failure. At the same time, the majority of runs are not followed by failure, highlighting that runs without failure are quite common.

Column 2 in Table 6 shows that banks with strong fundamentals have a significantly lower probability of failure. Moreover, the negative coefficient on $\text{Fundamentals}_{bt-1} \times \text{Run}_{bt}$ implies that strong fundamentals significantly reduce 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 are "strong", which we define as $\text{Fundamentals}_{bt-1}$ being in the upper tercile. We find that a run on a bank with strong fundamentals associated with only a 11% probability of failure, compared to 44% for banks with relatively weaker fundamentals. Thus, having strong observable fundamentals substantially reduces the probability of failure when a bank is exposed to a run.

Before proceeding, we note that this estimate is an 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.[26] Thus, this evidence does not imply that runs can cause the failure of healthy banks.

Column 4 of Table 6 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 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 38% probability of failure for a bank with weak fundamentals, but only a 6% probability of failure for a bank with strong fundamentals. Thus, for large banks, strong fundamentals appear to (nearly) fully insulate a bank from the risk of failure in response to a non-fundamental run.

Figure 5 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 75% 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. Thus, bank-specific fundamentals are central to understanding the pass-through of bank runs to failure.

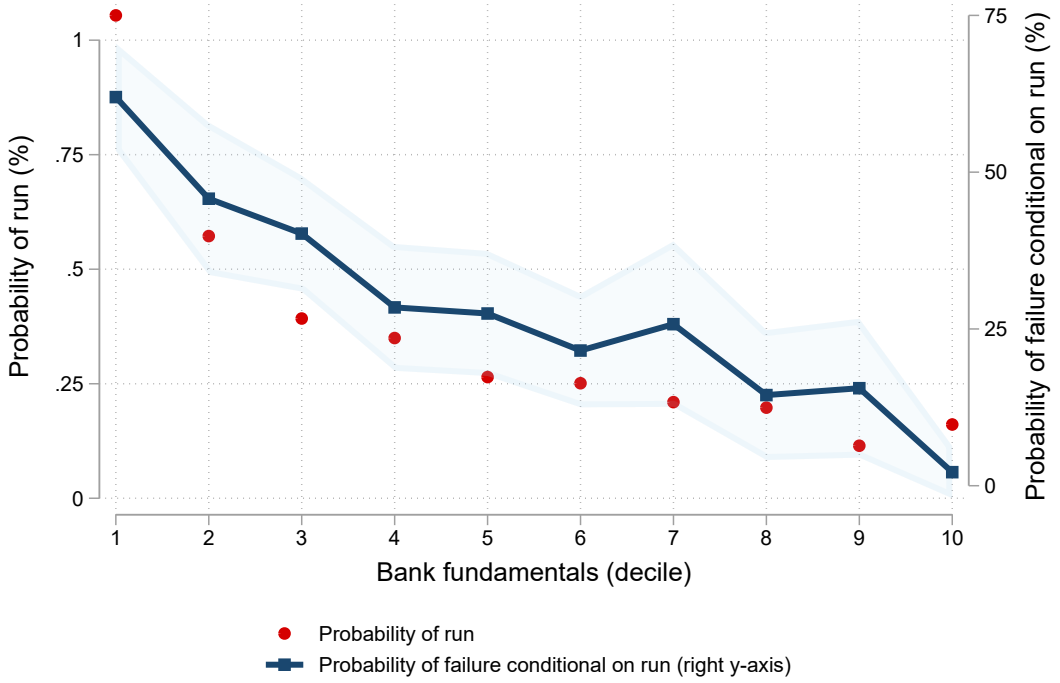
High Frequency Dynamics Figure 6 zooms in on the daily dynamics of the probability of failure around a run. In panel (a), we report the cumulative probability of bank failure around a run for all national banks from estimating local projections of the form:

$$\text{Failure}_{bt+h} = \beta^h \text{Run}_{bt} + \epsilon_{bt+h}, \qquad h = -5, ..., 40. \tag{5}$$

The probability of bank failure rises gradually to about 40% in the month following a run. Thus, essentially all failures following a run happen within a month of the run.

[26] 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.

Figure 5: ***Pass-Through of Runs to Failure across Deciles of Bank-Specific 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 $\text{Fundamentals}_{bt-1}$. $\text{Fundamentals}_{bt-1}$ is a proxy of bank health (see text). The sample consists of all national banks from 1863 through 1934. The shaded area represents 95% confidence intervals based on Driscoll-Kraay standard errors.

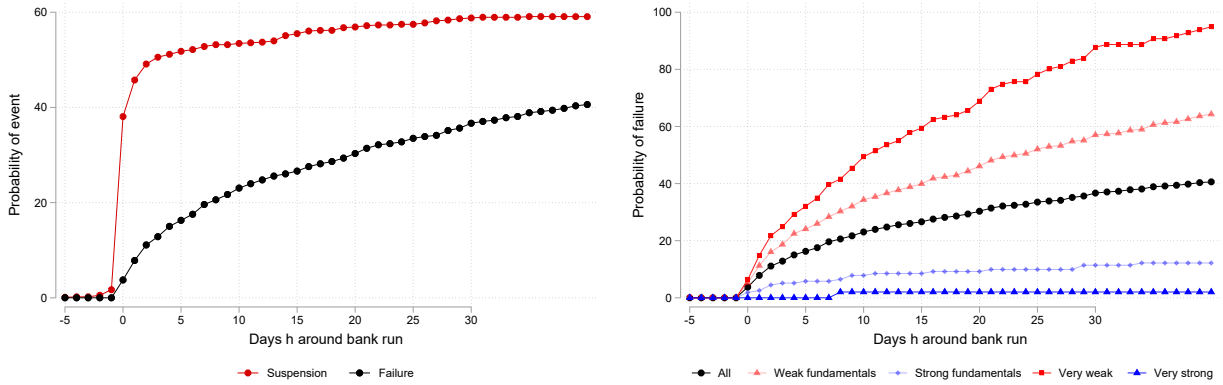
Figure 6 panel (a) also plots the probability of bank suspension. The dynamics of suspension display two differences compared to the dynamics of failure. First, suspension is more likely than failure, occurring after nearly 60% of runs. Second, suspension typically occurs immediately, within the same day or within a few days of the run. Nearly 40 percent of runs involve suspension on the same day.

Figure 6 panel (b) visualizes the cumulative probability of bank failure following a run across banks with weak and strong fundamentals. For each run occurring in year t, we split banks into the bottom decile (very weak), bottom tercile(weak), top tercile (strong), and top decile (very strong) of $\text{Fundamentals}_{bt-1}$, measured as of the most recent call report. The figure reinforces the striking difference in the likelihood of bank failure across weak and strong banks following a bank run. Very weak banks see a cumulative probability of failure of over 80%, while the probability is only about 6% for very strong banks.

Overall, this evidence indicates that, while runs can occur for strong and weak banks,

Figure 6: ***Daily Dynamics of Failure and Suspension Probability around Bank Run***

(a) *Bank runs, suspensions, and bank failures* **(b)** *Bank failure after runs by fundamentals*



Notes: Both panels plot coefficients from estimating (5). In panel (a), we report results with failure and suspension as the outcome variables. In panel (b), we estimate the local projections separately for banks with weak and strong fundamentals, based on the upper and lower terciles of the Fundamentals$_{bt-1}$ measure.

they are substantially more likely to occur in weak banks, consistent with theories of fundamental-based panic runs. Moreover, conditional on a run, a weak bank is much less likely to survive the runs. Thus, the combination of these two findings implies that runs almost never trigger the failure of strong banks.

Event Study of Fundamentals around Runs and Failures Appendix A.1 provides further illustration of the marked differences in bank fundamentals across banks subject to runs that fail and those that survive. We conduct simple event studies of bank fundamentals around runs without failure and runs with failure. Banks subject to runs that do not fail look similar to ordinary banks not subject to any form of distress. In contrast, banks that fail with a run have both worse fundamentals and are on a worse trajectory of deteriorating fundamentals. This evidence reinforces the finding that poor fundamentals are key to determining whether a bank will fail. Runs that do not result in failure tend to occur in healthy banks, while runs that result in failure occur in observably weak banks.

6.2 Non-Fundamental Runs and Bank Failures

Can non-fundamental runs trigger bank failures? To answer this question, we use textual analysis to classify a subset of the runs in our dataset as non-fundamental runs. We define a non-fundamental run as a run where newspapers affirmatively describe that the run was triggered by a specific, discrete episode of misinformation or confusion that

triggered withdrawals and the source explicitly indicates that it was false, mistaken, or later corrected. These non-fundamental runs are *not* triggered by adverse news about the bank, failures or distress of other banks, systemic panic, or local economic shocks. See the prompt in Appendix B.1 for the exact definition used in the classification. We identify 40 runs on national banks that are classified as non-fundamental, indicating that such runs are uncommon. We manually checked each of these runs to ensure there are no false positives. Figure B.8 provides examples of non-fundamental runs.

Table 6: ***Pass-Through of Runs to Failure: Narrative Classification of Non-fundamental Runs***

Dependent variable	Failure in t+1		
	(1)	(2)	(3)
Run	0.39***		
	(0.053)		
Non-fundamental run		0.13**	0.17**
		(0.049)	(0.068)
Other run		0.40***	0.45***
		(0.055)	(0.055)
Strong Fundamentals			-0.0100**
			(0.0040)
Strong Fundamentals × Non-fundamental run			-0.17**
			(0.068)
Strong Fundamentals × Other run			-0.33***
			(0.048)
Observations	265717	265717	265717
Mean dep. var.	0.0085	0.0085	0.0085

Notes: This table presents estimates of Equation (6). Driscoll-Kraay standard errors in parentheses. *,**, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table 6 studies the pass-through of non-fundamental runs to bank failure based on estimating

$$\text{Failure}_{bt} = \beta_0 + \beta_1 \text{Non-Fundamental Run}_{bt} + \beta_2 \text{Other Run}_{bt} \epsilon_{bt}, \tag{6}$$

While the typical run is our sample is associated with a probability of failure of 37%, this drops to 12% for non-fundamental runs. Thus, non-fundamental runs are much less likely to result in bank failure. Moreover, column 3 shows that strong banks subject to non-fundamental runs have a zero probability of failure. Thus, non-fundamental runs can sometimes trigger failure if they happen to affect weak banks. In our review of these cases, one non-fundamental run happened to trigger failure because it spurred an examination that revealed fraud.[27]

[27]For example, the First National Bank of Sedalia was subject to a run in May 1894 following the

6.3 Adverse Public Signals, Runs, and Failures

We next study the pass-through of runs into failure for runs associated with adverse public signals. Table 7 presents results from estimating variants of the following specification

$$\begin{aligned} \text{Failure}_{bt} = \beta_0 + \beta_1 \text{Run}_{bt} + \beta_2 \text{AdverseSignal}_{rt} \\ + \beta_3 \text{Run}_{bt} \times \text{AdverseSignal}_{rt} + \epsilon_{bt}, \end{aligned} \tag{7}$$

where $\text{AdverseSignal}_{rt}$ is an aggregate or regional adverse public signal, such as a run on another bank in the same city. This specification asks whether the pass-through from runs to failure differs for runs occurring after adverse public signals that are not bank-specific.

Table 7: ***The Pass-Through of Runs to Failure: The Role of Adverse Public Signals***

Dependent variable	Failure in t+1					
	(1)	(2)	(3)	(4)	(5)	(6)
Run	0.39***	0.43***	0.43***	0.30***	0.19***	0.24***
	(0.053)	(0.046)	(0.046)	(0.050)	(0.056)	(0.051)
Run on other bank in same city		0.016***	0.35***			0.021***
		(0.0053)	(0.13)			(0.0062)
Run on other bank in same city × Run		-0.17***	-0.42***			-0.17***
		(0.035)	(0.13)			(0.033)
Run on other bank before run × Run			-0.15**			
			(0.064)			
Local business failure rate				0.77***		0.27**
				(0.18)		(0.12)
Local business failure rate × Run				5.42***		1.75**
				(1.28)		(0.77)
Business failure rate					1.31***	1.07**
					(0.36)	(0.43)
Business failure rate × Run					10.9***	8.88***
					(2.31)	(1.86)
Observations	275178	275178	275178	236300	240691	236300
Mean dep. var.	0.0083	0.0083	0.0083	0.0092	0.0091	0.0092

Notes: This table presents results from estimating variants of Equation (7). Driscoll-Kraay standard errors in parentheses with three lags. *,**, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

In Table 3, we saw that the occurrence of a run in the same city was one of the strongest non-bank-specific antecedents of a run. Column 2 in Table 7 shows that runs that coincide with a run on another bank in the same city are 17 pp *less* likely to result in failure. This

publication of a false rumor in the form of a "fake" telegram that the bank had failed. The bankers were later charged with fraud. The depositor recovery rate for this failure was 18% (not adjusted for the delay in payment), indicating deep insolvency. See description here: https://www.finhist.com/bank-runs/episodes/11443.html.

is driven by runs that occur *after* a run on another bank. The lower probability of failure for such runs is consistent with the notion that a run on another bank leads depositors to become "jittery." They revise upward their belief that their own bank is insolvent. However, in some cases, this signal that is not bank-specific leads depositors to mistakenly run on healthy banks, so these runs are less likely to lead to failure.

In column 4 of Table 7, we use the state-level nonfinancial business and national bank failure rates as the proxy of economic conditions. In contrast to the finding for runs on other banks, we find that runs that occur when the state-level business failure rate is elevated are *more* likely to be associated with a bank failure. A rise in state-level business failures signals an increase in bank asset losses and thus an increased risk of bank insolvency. Runs in response to this deterioration of economic fundamentals are more likely to translate to failure, as these are precisely the times when banks are more likely to be insolvent. Columns 5 and 6 reveal a similar pattern when we use the aggregate nonfinancial business failure rate, rather than the local failure rate.

To further illustrate that bank runs and failures often follow a rise in non-financial business failures, Figure 7 shows the dynamics of the state-level non-financial business failure rate around innovations in the state-level rate of bank runs and bank failures. This analysis is based on estimating local projections in a state-level quarterly panel of the form

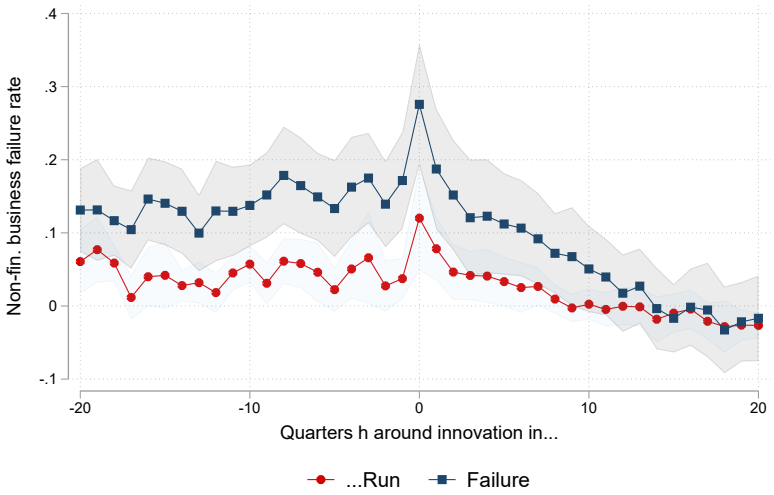
$$\text{Business Failure Rate}_{st+h} = \alpha_s + \text{Bank Distress}_{st} + u_{t+h}, \quad h = -20, ..., 0, ..., 20, \quad (8)$$

$\text{Business Failure Rate}_{st+h}$ is the state-level non-financial business failures rate in state s for quarter $t+h$, and $\text{Bank Distress}_{st}$ is the share of banks exposed to a run or failure in state s and quarter t.

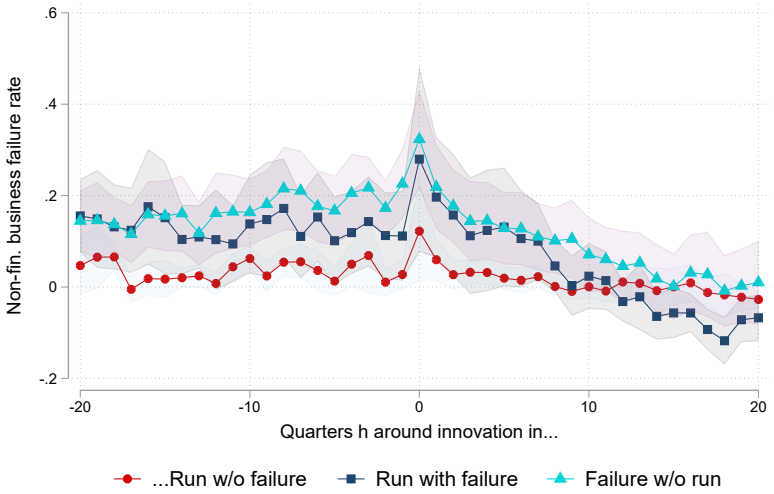
Figure 7 shows that both bank runs and bank failures are preceded by an elevated rate of business failures. This is especially strong for bank failures. Bank failures follow a rise in non-financial firm defaults, which lead to asset losses for banks. Both runs and failures tend to occur alongside spikes in the rate of non-financial business failures ($h = 0$). This evidence supports the key role of deteriorating fundamentals for understanding bank failures and runs in response to the elevated likelihood of failure. The small spike in business failures around runs without failure further suggests that increases in business failures can lead to runs on healthy banks that do not ultimately fail, consistent with information-based theories of runs.

Figure 7: ***Dynamics of State-level Non-financial Business Failure Rate around Innovations in Bank Runs and Failures***

(a) *Runs versus failures*



(b) *Runs with failure, runs without failure, and failure without runs*



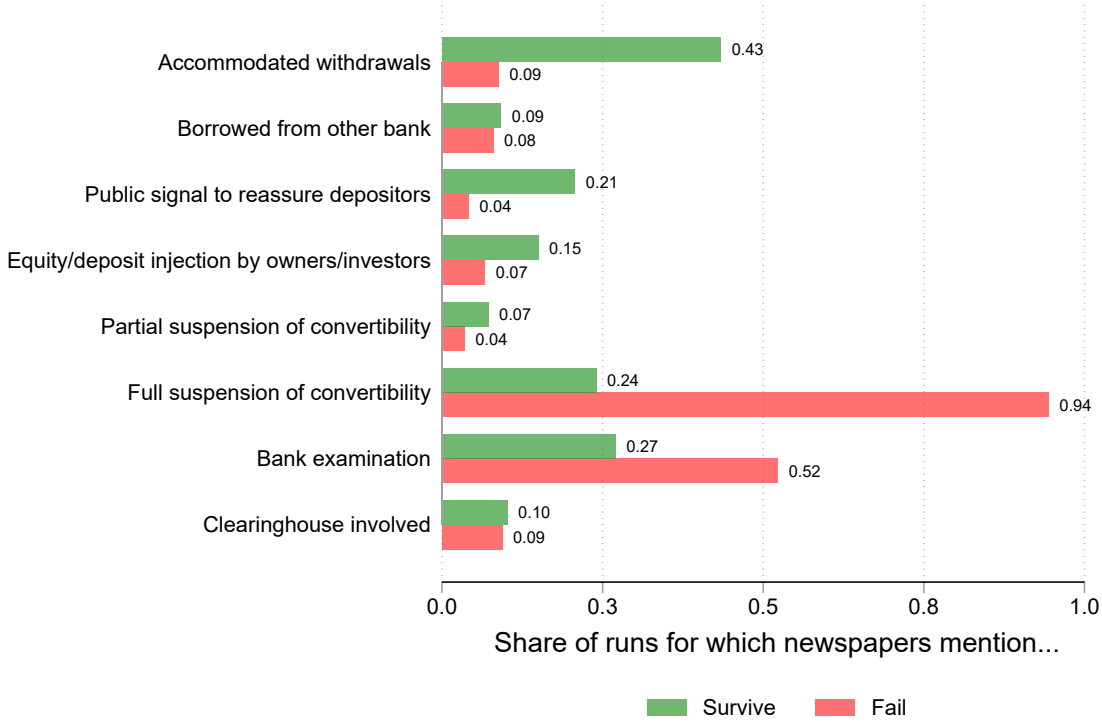
Notes: This figure plots the dynamics of the state-level non-financial business failure rate around innovations in the rate of bank runs and bank failures. Coefficients are based on estimation of (8). The non-financial business failure rate is defined as the number of business failures relative to the total number of manufacturing establishments in a state. Error bands represent 95% confidence intervals based standard errors dually clustered on state and quarter. The specification also controls for quarter fixed effects to capture seasonability in the failure rate.

6.4 Bank Responses to Runs

How do banks respond to runs? What actions do strong banks take to avoid failing during runs? To answer these questions, we revisit the newspaper texts. After reading hundreds of newspaper descriptions of runs, we identified seven common responses described

in newspapers: (i) the bank accommodated withdrawals by paying out depositors; (ii) the bank borrowed from another bank; (iii) the bank sent a public signal to reassure depositors, such as a conspicuously delivering gold or cash to the bank; (iv) bank owners or investors injected equity or provided a loan; (v) partial suspension of convertibility; (vi) full suspension of convertibility; and (vii) the bank underwent an examination by state supervisors, federal examiners, or by the local clearinghouse to ascertain its solvency. These responses are not mutually exclusive. We query an LLM to identify whether the newspaper description of a bank run episode mentions any of seven potential bank responses. See Appendix B for the exact prompts we use.

Figure 8: ***Responses to Bank Runs by Failing and Surviving Banks Discussed in Newspapers***



Notes: This figure plots the share of episodes involving a bank run in which the newspapers mention one of the listed actions. The shares are reported separately for runs without and with failure.

Figure 8 reports the share of run episodes mentioning each of these responses. We distinguish between runs that result in failure and those where the bank survives. The results are intuitive. Banks that survive runs are more likely to be described as accommodating withdrawals compared to banks that fail in the run. Banks that survive runs are also more likely to send a public signal to reassure depositors, such as delivering a "truckload of cash" to the bank. Bank owners or investors also often inject additional equity into the bank. Surviving banks often take several of these actions in conjunction to

ward off a run (see Figure A.8). Surviving banks are also more likely to partially suspend convertibility, though this action is relatively uncommon.

In contrast, newspapers are substantially less likely to report that banks that fail in a run take these actions. Instead, newspapers emphasize that these banks are likely to fully suspend convertibility of deposits into currency. Moreover, banks that fail are also more likely to be subject to an examination by state supervisors, federal examiners, or the local clearinghouse to evaluate if the bank is solvent. When these banks are deemed to be insolvent, they are then closed. Finally, in about 10% of runs, newspapers explicitly mention clearinghouse involvement, either through the provision of a loan, examination, or other measure.[28]

7 Consequences of Bank Runs for Deposits and Lending

This section studies the consequences of runs and failures. 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 on local aggregate lending and deposits.

7.1 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:

$$\frac{Y_{bt+h} - Y_{bt-1}}{\text{Assets}_{bt-1}} = \alpha_b + \gamma_t + \beta^h \text{Run w/o failure}_{bt} + \epsilon_{bt+h}, \quad h = -5, \ldots, 5 \tag{9}$$

with the prediction horizon h running from five years before to five years after the distress episode. Run w/o failure$_{bt}$ is an indicator variable equal to one for a bank run without failure. We focus on runs without failure to understand the consequences of runs for surviving banks. 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, 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

[28]Table A.9 examines whether the pass-through of runs to failure is lower for banks that are likely to be part of a local clearinghouse. Banks in cities with a clearinghouse were more likely to survive a run, suggesting that clearinghouses mitigated the effect of runs. This effect may be explained by the ability of clearinghouses to provide emergency liquidity as well as to credibly examine and transmit information about member banks' health.

this regression. Runs without failure may result in a contraction in lending through a reduction in bank credit supply. However, as we have shown, runs without failure often occur in response to bad news about the economy that leads depositors to run as a precautionary measure. These shocks can simultaneously reduces demand for loans and deposits.

To study the consequences of a bank run without failure that is exogenous to bank and economic fundamentals, we replace the shock with our measure of non-fundamental runs discussed in Section 6.2. These runs, caused by false rumors or misinformation, are more exogenous events not caused by bank or economic conditions. This allows us to trace the effects of runs that are closer in spirit to the notion of random runs in Diamond and Dybvig (1983). In particular, we estimate:

$$\frac{Y_{bt+h} - Y_{bt-1}}{\text{Assets}_{bt-1}} = \alpha_b + \gamma_t + \beta^h_{NF}\text{Non-fund run w/o failure}_{bt} + \beta^h_{Other}\text{Other run w/o failure}_{bt} + \epsilon_{bt+h}, \quad h = -5, \ldots, 5. \tag{10}$$

Figure 9a shows the results from estimating Equation (10) for deposits and loans on the 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.

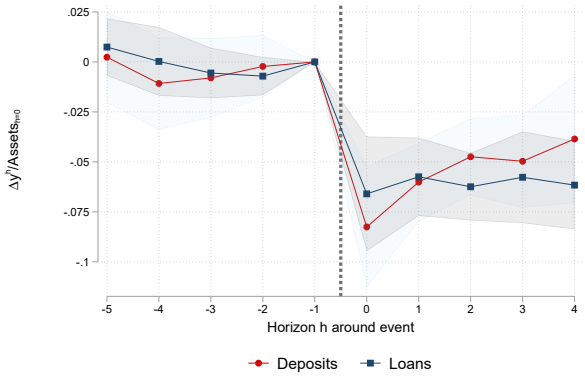
Figure 9b explores heterogeneity across runs with and without suspension. "Run-only" episodes in which the bank is run but does not suspend have relatively mild reductions in deposits. After these episodes, banks recover their deposits within five years. Episodes with a run, suspension, and reopening are more severe, leading to a 15 percent decline in deposits that persists for five years.

Figure 9 panels (c) and (d) study the consequences of non-fundamental runs and other runs by estimating Equation (10). Non-fundamental runs without failure lead to a 5% drop in deposits and loans, similar to other runs without failure. Interestingly, deposits of banks subject to non-fundamental runs recover fully within four years of the run, similar to "run only" events (see panel b). Loans remain roughly 5% lower three years after the run. Thus, runs that we specifically identify as non-fundamental and that are thus exogenous to bank and local economic conditions do lead to moderate disruptions in bank-level deposits and credit.

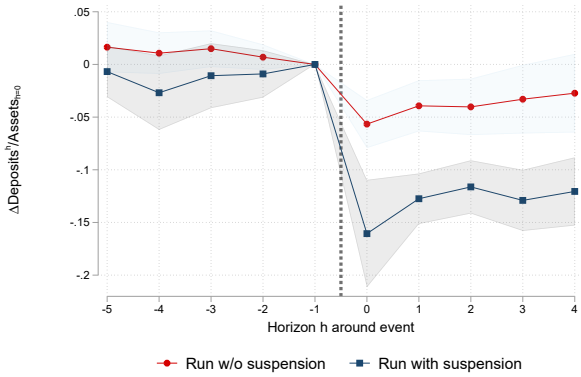
What are the implications of a run without failure across weak and strong banks? To

Figure 9: ***Bank-Level Deposit and Loan Dynamics around Bank Runs Without Failure***

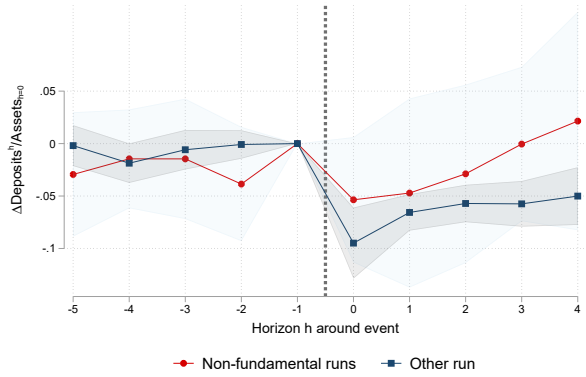
(a) *Deposits and loans: bank runs without failure*



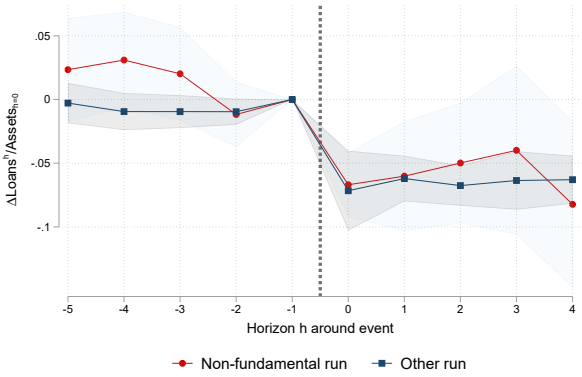
(b) *Deposits: bank runs with and without suspension*



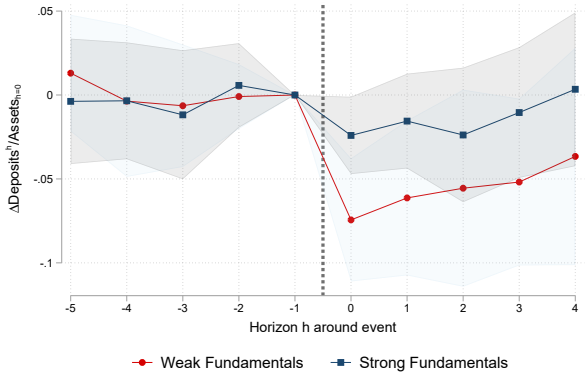
(c) *Deposits: non-fundamental runs and other runs*



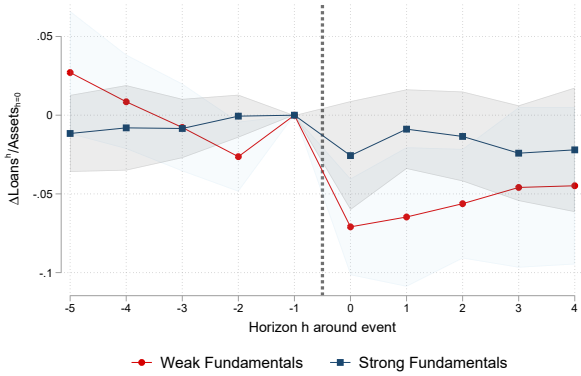
(d) *Loans: non-fundamental runs and other runs*



(e) *Deposits: weak vs strong banks*



(f) *Loans: weak vs strong banks*



Notes: This figure reports coefficients from estimating Equations (9) (panels a and b), (10) (panels c and d), and (11) (panels e and f). All episodes are runs without bank failure. Shaded areas represent 95% confidence intervals based on standard errors dually clustered on bank and year. Strong and weak fundamentals are based on top and bottom tercile of Fundamental

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

$$\frac{Y_{b,t+h} - Y_{b,t-1}}{\text{Assets}_{b,t-1}} = \alpha_b + \gamma_t + \beta_S^h \text{Run}_{b,t} \times \text{Strong Fundamentals}_{b,t-1} + \beta_W^h \text{Run}_{b,t} \times \text{Weak Fundamentals}_{b,t-1} + \epsilon_{b,t+h}, \qquad h = -5, \ldots, 5 \tag{11}$$

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

Figure 9 panels (e) and (f) present the results. Runs without failure lead to larger deposit declines for banks with weak fundamentals. Banks with strong fundamentals see essentially no decline in loans and deposits, whereas banks with weak fundamentals see a persistent decline in deposits and lending of about 7%. Thus, bank fundamentals not only determine whether runs trigger bank failure; they also shape the consequences of bank runs when banks survive runs.

7.2 Local Economic Consequences of Runs and Failures

As a final exercise, we examine the consequences of bank runs and failures at the local economic level. There is considerable time-series and cross-sectional variation in state-level exposure to bank distress episodes (see Figure A.10). In most years, the typical state has no bank distress episode, even during banking crisis years. During crisis years, the number of episodes spikes in the upper tail of the distribution. 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:

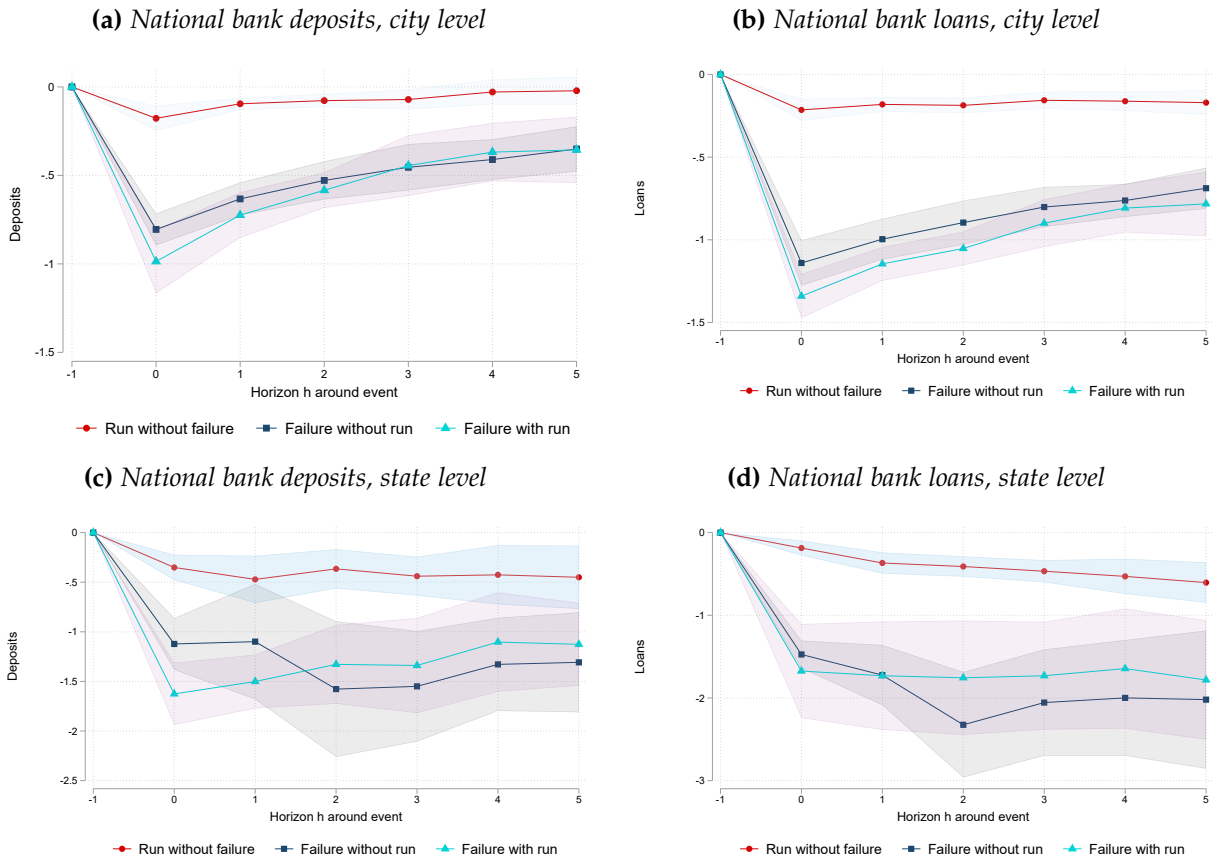
$$\begin{aligned} y_{c,t+h} =& \alpha_i + \gamma_b + \beta_0^h \text{Bank Distress}_{c,t} \\ &+ \sum_{l=1}^{L} \left[\delta_l^h y_{c,t-j} + \beta_l^h \text{Bank Distress}_{c,t-l} \right] + \epsilon_{c,t+h}, \quad h = 0, ..., H \end{aligned} \tag{12}$$

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 $L = 3$ lags of both the shock and the dependent variable, as is standard in the local projections framework (Jordà, 2005).

The shock, Bank Distress$_{c,t}$, is the asset-weighted share of banks in a region (city or state) subject to a particular distress event. Therefore, Bank Distress$_{c,t}$ 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. $y_{c,t}$ is based on the aggregate of national bank balance sheets at the city or state level.

Figure 10 presents the results for loans and deposits at the city and state level. At

Figure 10: ***Consequences of Runs and Failures at the Local Level***



Notes: This figure presents impulse responses based on estimation of Equation (12). The analysis is based on a city or state level annual panel. Loans, deposits, and bank distress are based on aggregating the sample of national banks from 1863-1934. Error bands represent 95% confidence intervals based on standard errors clustered at the city or state level.

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 10 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 10 shows that if 10% of a city's banks fail without a bank run, total deposits decline immediately by around 7% and loans fall by 11%. If 10%

of all banks fail *with* a bank run, deposits decline by around 10% and loans by 13%. In both cases, the effect is persistent, although there is a slight recovery. After 5 years, total loans will remain around 7% 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 slightly below trend.

8 Conclusion

In this paper, we apply natural language processing to historical newspapers to study bank runs in 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. Strong banks manage to survive runs through various mechanisms, interbank cooperation, equity injections or loans, examination, and suspension. Furthermore, healthy banks 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. At the local level, bank runs without failure appear more benign than bank runs with bank failure or even bank failures without runs. 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.

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Bank Runs, Failures, and the Real Economy

Online Appendix

Sergio Correia, Stephan Luck, and Emil Verner*

- Appendix A: Additional results, figures, and tables.
- Appendix B: Constructing the bank distress episodes dataset.

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A Additional Results

A.1 Discussion of Selected Appendix Results

Event Study of Bank Fundamentals around 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 types. Specifically, we estimate specifications of the following form:

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

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 A.6 plots the coefficients from estimating Equation (A.1) 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 A.6 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 slightly stronger 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 3. 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 A.6 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 A.6 shows that failing banks face a decline in their deposit-to-assets ratio of about 4 points before failure.[1] 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 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

[1]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.

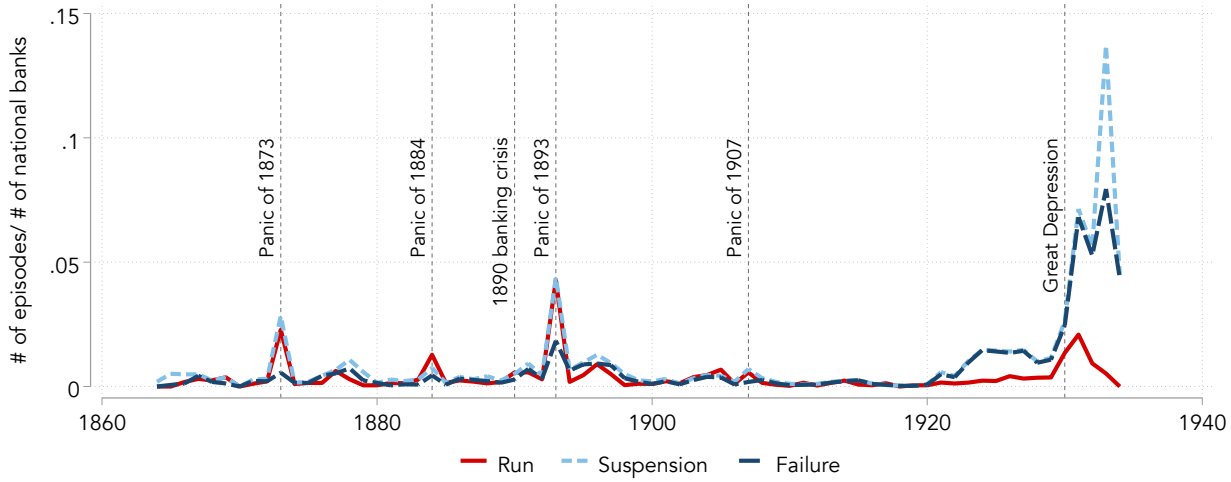
subject to runs that do not fail. Banks subject to runs that do not fail look similar to ordinary banks not subject to any form of distress. Moreover, failing banks have weak bank observables, irrespective of whether they are subject to a run before failure.

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, there is suggestive evidence that runs trigger the failure of slightly healthier banks, on the margin, as observables are slightly better for banks that fail with a run compared to those that fail without a run. This suggests that runs may slightly accelerate the failure of weak banks. However, given that these banks are on similar trajectories, banks that fail with a run might have failed even in the absence of the run, but the run accelerated their demise. At the same time, we do not want to overstress this finding. When we classify failures with and without runs based on the size of deposit outflows in the run-up to failure, the differences across the two types of failure become even smaller and are no longer statistically significant (see, e.g., Correia et al., 2026).

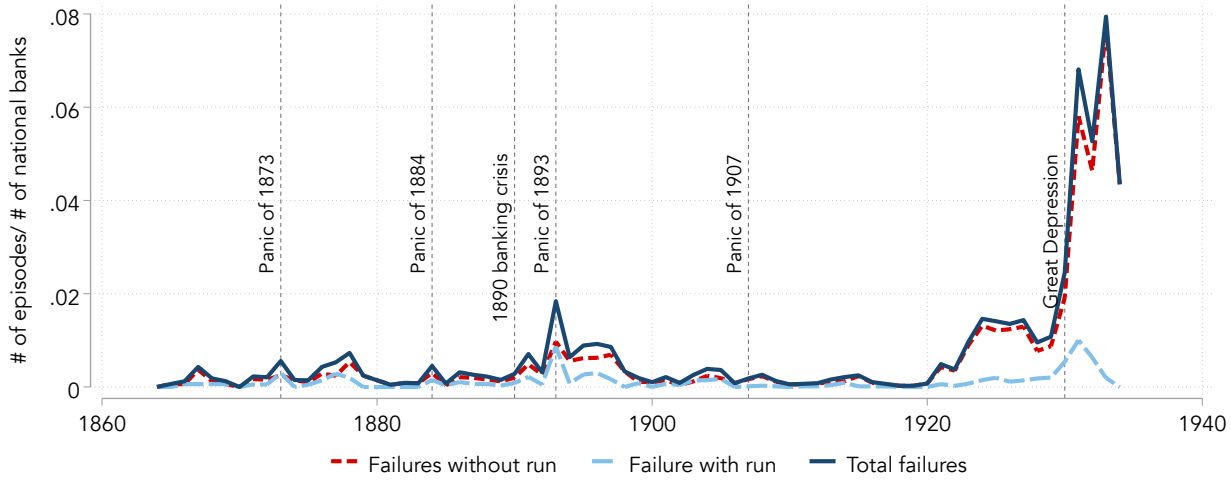
A.2 Additional Figures

Figure A.1: ***Bank Runs, Suspensions, and Failures for National Banks, 1863-1934***

(a) *Runs, suspensions, and failures*

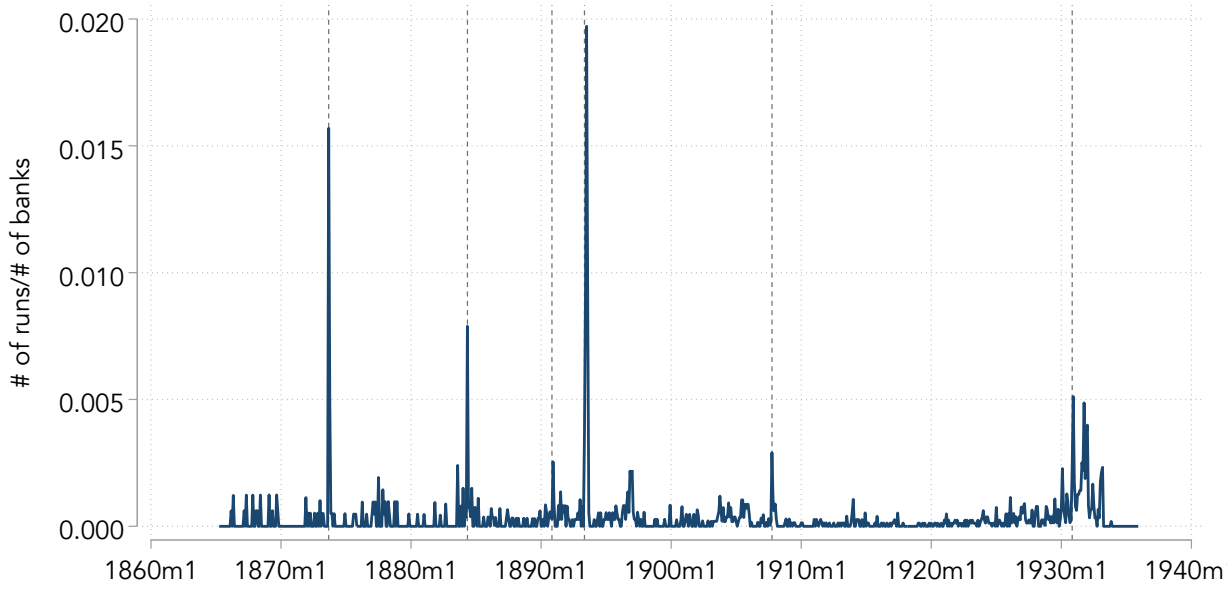


(b) *Failures with and without runs*



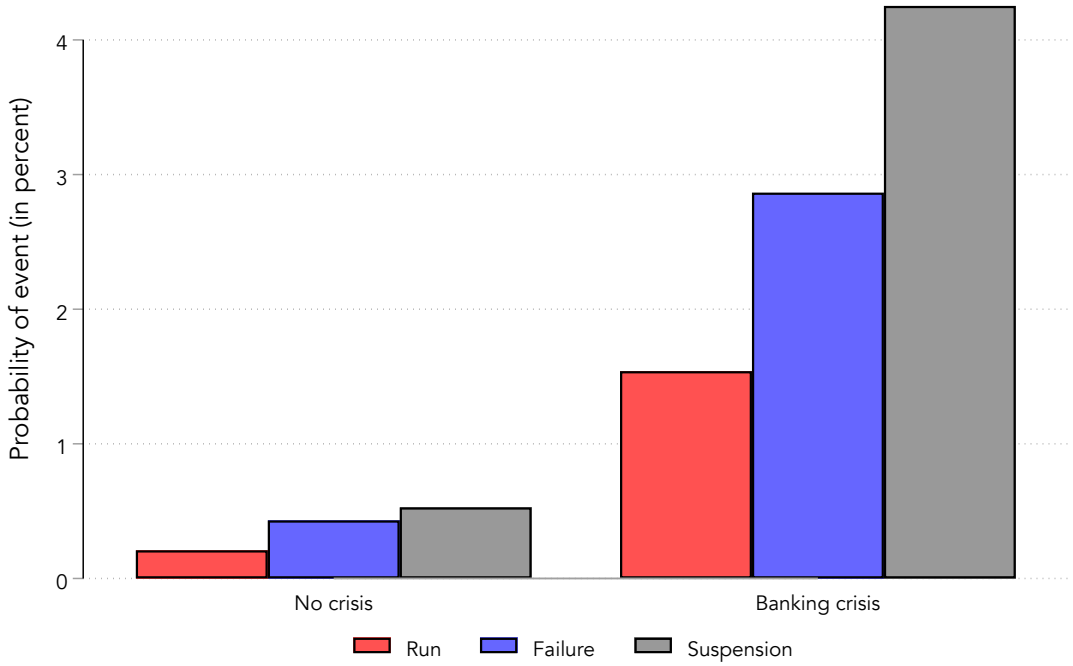
Notes: This figure plots the ratio of the number of national banks subject to a distress episode over the total number of national banks in each year. In panel (a), we report the rate of bank runs, suspensions, and failures. In panel (b), we show the number of bank failures (OCC receiverships) that are associated with runs reported in newspapers and those that are not associated with runs.

Figure A.2: ***Bank Runs Rate, Monthly Time Series for National Banks***



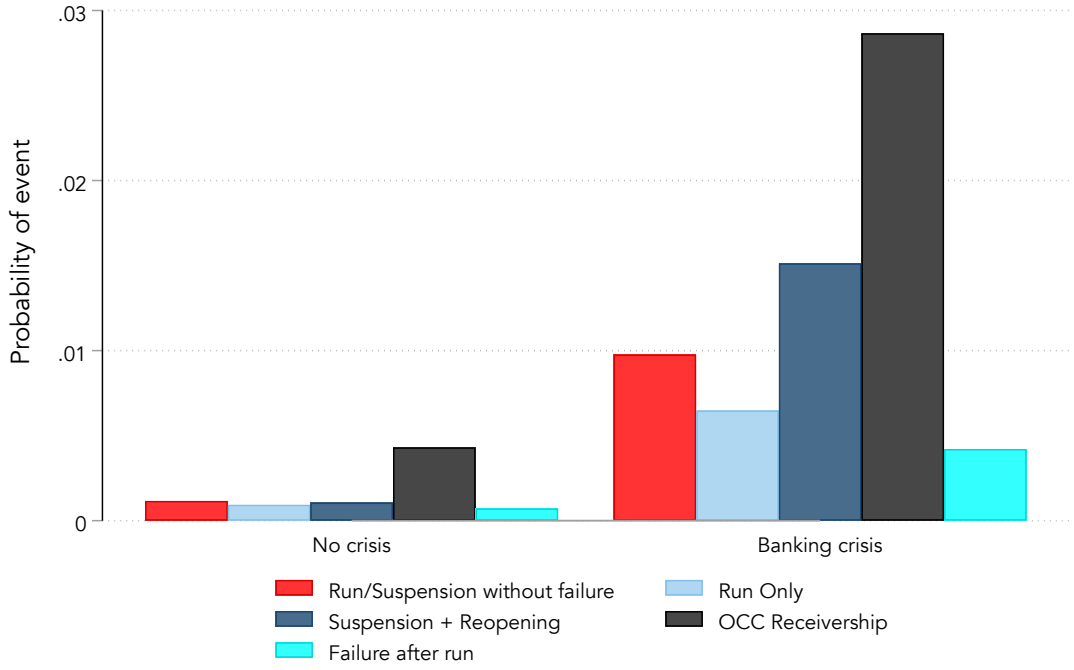
Notes: Vertical lines represent the month of a banking panic from Baron et al. (2021).

Figure A.3: ***Probability of Runs, Suspensions, and Failures National Banks During and Outside of Banking Crises***



Notes: The figure plots the probability of bank runs (both 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 all national banks during 1863-1934.

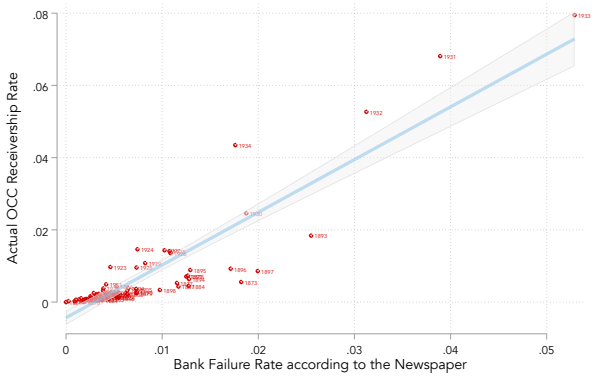
Figure A.4: ***Probability of Bank Distress Episodes for National Banks During and Outside of Banking Crises***



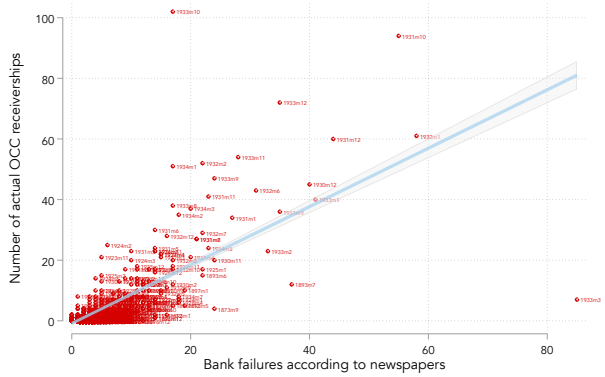
Notes: The figure plots the probability of various bank distress episodes during and outside of years identified as banking crises in Baron et al. (2021). The sample is based on all national banks from 1863-1934.

Figure A.5: *Data Quality Validation*

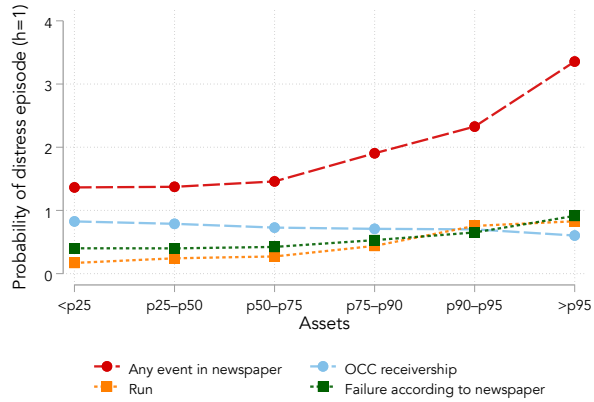
(a) *National Bank Failure Rates: Annual*



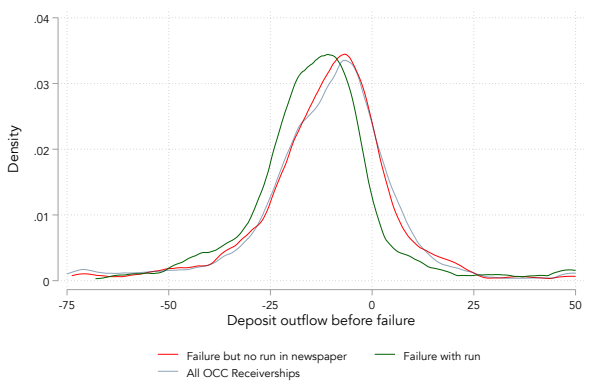
(b) *Number of National Bank Failures: Monthly*



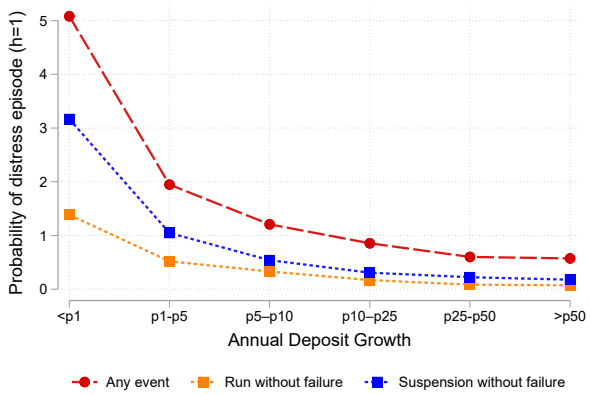
(c) *Events by Size*



(d) *Deposit Outflows*



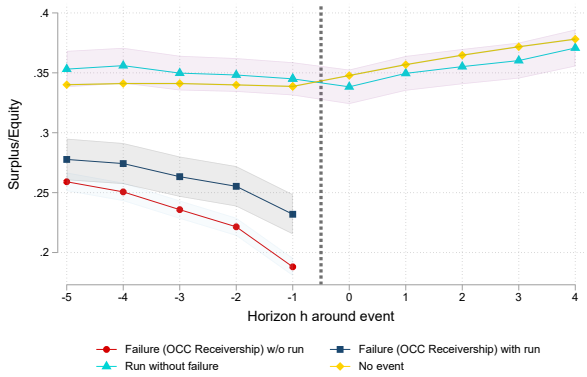
(e) *Probability of distress event as a function of deposit growth*



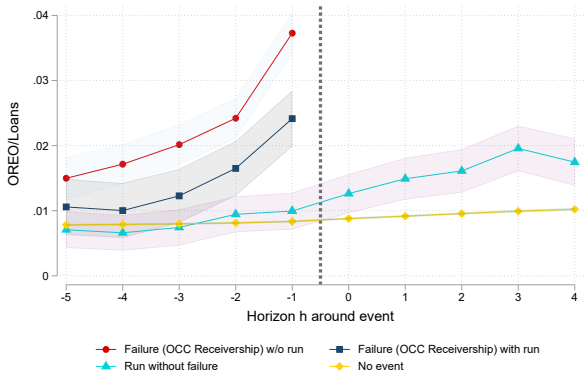
Notes: The sample in all panel is based on national banks during 1863-1934. In panel (d), the sample is all OCC national bank receiverships during 1864-1934. Deposit outflows before failure are calculated using the total deposits reported in the last call report before failure and deposits at failure.

Figure A.6: ***Characteristics of Banks Subject to Runs With and Without Failing***

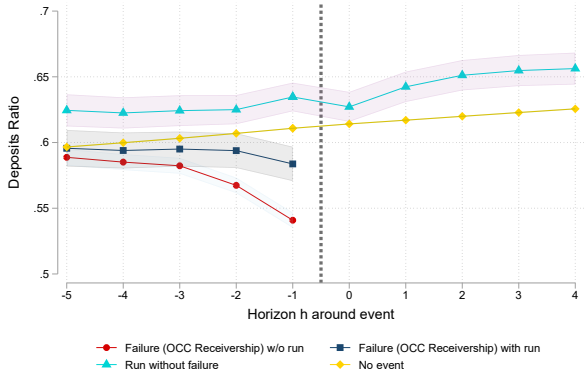
(a) *Surplus/Equity*



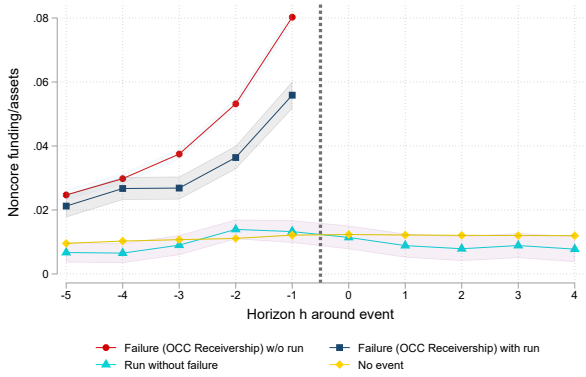
(b) *Non-performing loans/Loans*



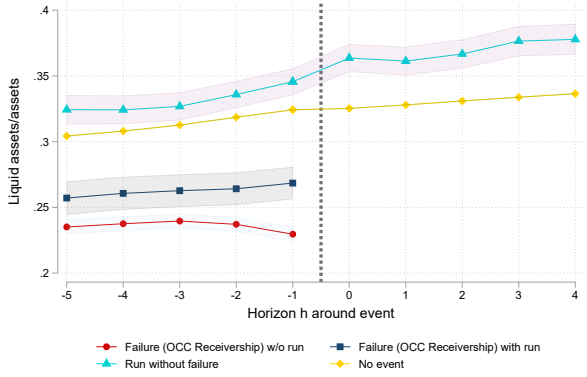
(c) *Deposit/Assets*



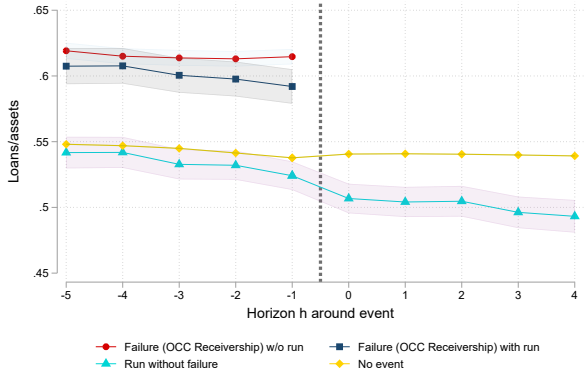
(d) *Noncore Funding/Assets*



(e) *Liquid/Assets*

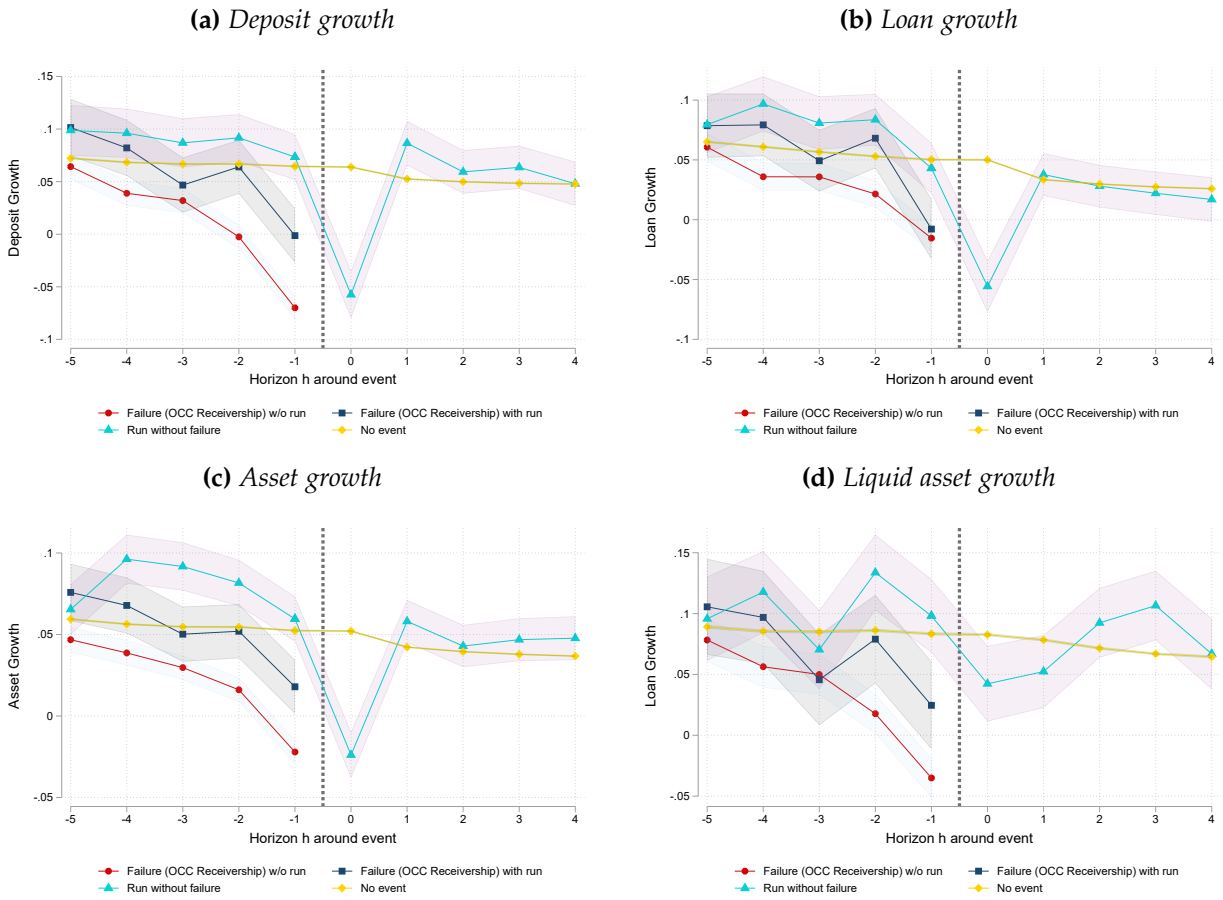


(f) *Loans/Assets*



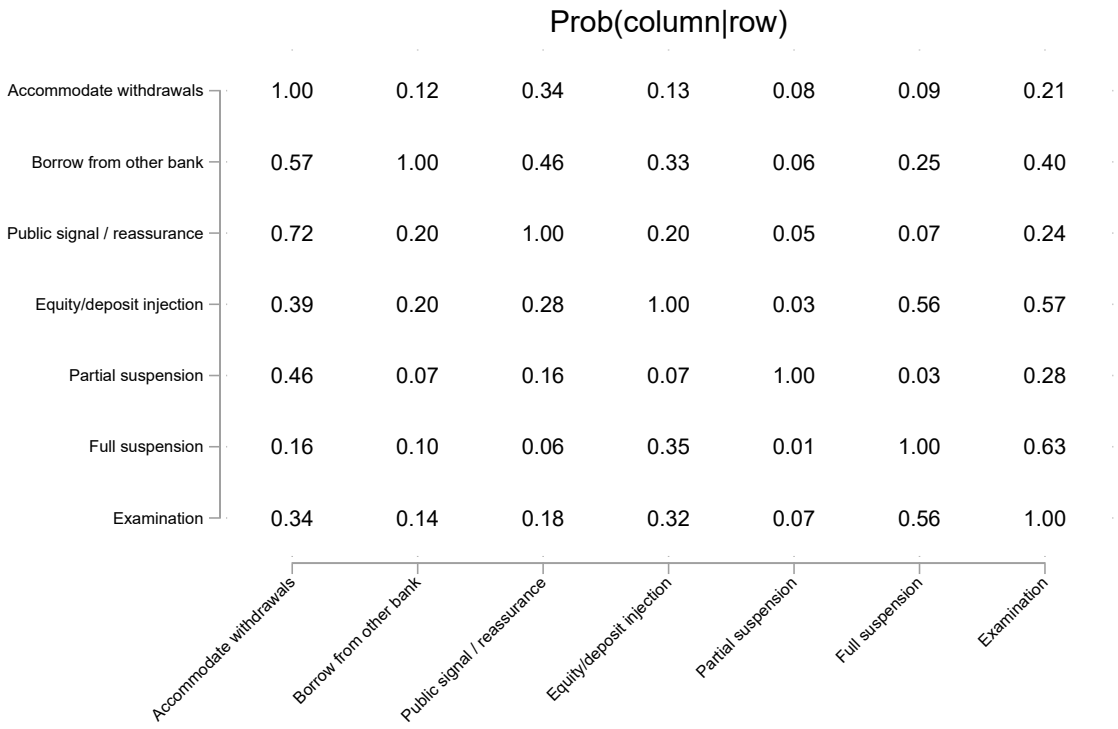
Notes: This figure plots the coefficients from estimating Equation (A.1). Non-performing loans are proxied by the line item "other real estate owned" (OREO). Shaded areas represent 95% confidence bands. Figure A.7 shows the same plot using the deposit, loan, assets, and liquid assets grwoth as the outcome variable.

Figure A.7: ***Characteristics of Failing Banks and Banks Subject to Runs that Survive around Distress Events: Growth Rates***



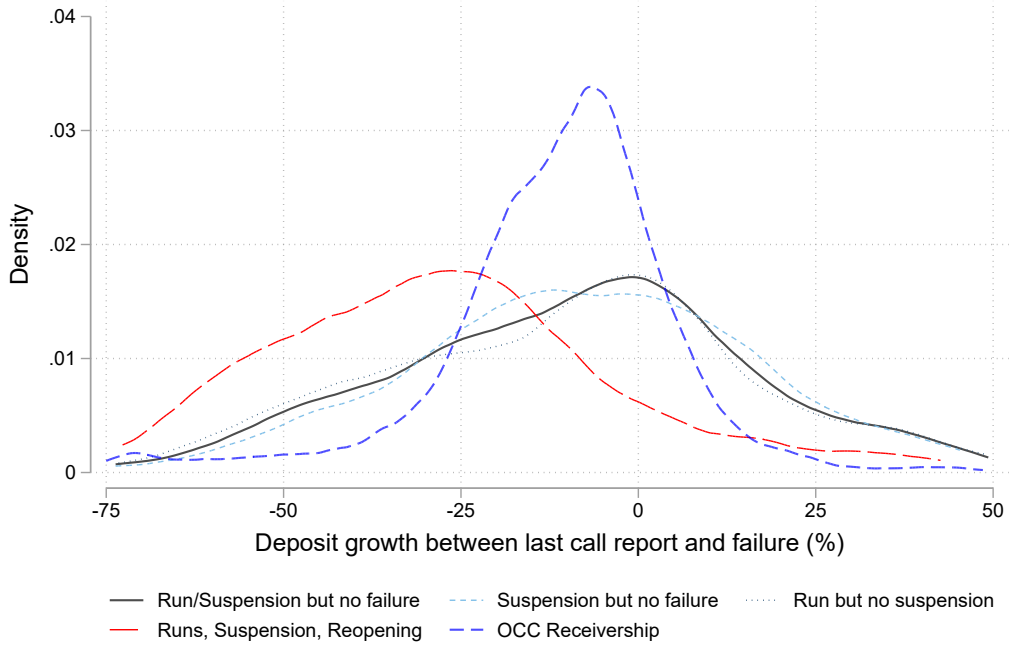
Notes: This figure plots the coefficients from estimating Equation (A.1). Shaded areas represent 95% confidence bands.

Figure A.8: ***Responses to Bank Runs: Conditional Probabilities***



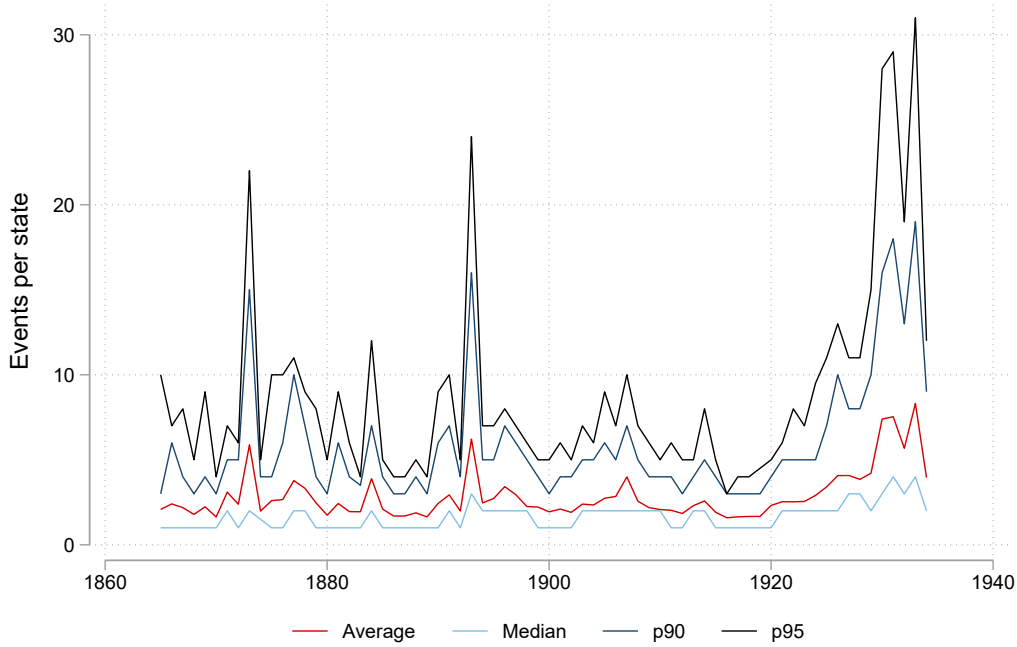
Notes: This figure reports the probability of a response listed in each column, conditional on the bank taking the response in a given row. See Figure 8 for further details on the classification of responses.

Figure A.9: *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.10: *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.

A.3 Additional Tables

Table A.1: ***Narrative Banking Crisis Classifications and Bank Distress Events***

Dependent variable	Run	Failure	Suspension
	(1)	(2)	(3)
Major banking crisis year	0.49***	0.68***	1.36***
	(0.061)	(0.16)	(0.19)
Major banking panic month	2.01**	-0.59***	2.07**
	(0.83)	(0.19)	(0.81)
May 1884 (NYC, PA, NJ)	13.2*	2.86***	8.15**
	(7.30)	(0.68)	(3.93)
Nov. 1890 (New York City, NY)	0.75	0.90***	0.35
	(0.45)	(0.13)	(0.43)
Dec. 1896 (IL, MN, WI)	8.75**	4.95**	9.91***
	(3.33)	(1.98)	(3.57)
Dec. 1899 (Boston, MA; NYC, NY)	2.75*	3.78**	6.24***
	(1.44)	(1.80)	(0.72)
June through July 1901 (NY: Buffalo; NYC)	0.75***	6.28***	6.24***
	(0.023)	(0.043)	(0.037)
Oct. 1903 (PA, MD)	1.75***	-0.72***	0.24***
	(0.023)	(0.043)	(0.037)
Dec. 1905 (Chicago, IL)	1.25***	0.78***	3.24***
	(0.023)	(0.043)	(0.037)
Jan. 1908 (NYC)	2.75***	5.28***	10.2***
	(0.023)	(0.043)	(0.037)
Aug. through Sept. 1920 (Boston)	4.75***	1.28***	3.24***
	(0.023)	(0.043)	(0.037)
Nov. 1920 - Feb. 1921 (ND)	1.75***	2.28***	10.2***
	(0.023)	(0.043)	(0.037)
July 1926 (FL, GA)	2.75***	-0.72***	3.24***
	(0.023)	(0.043)	(0.037)
March 1927 (FL)	10.7***	0.28***	16.2***
	(0.023)	(0.043)	(0.037)
July through Aug. 1929 (FL)	21.7***	7.28***	26.2***
	(0.023)	(0.043)	(0.037)
N	11318	11318	11318
Mean dep. var.	0.40	0.86	1.09

Notes: This table shows results from estimating Equation (1) using a monthly state-level panel with the number of distress events as the outcome variable. Major banking crises and major banking crises panic month are taken from Baron et al. (2021) and regional banking crises are from Jalil (2015). Sample of events 1863 through 1934. Standard errors clustered at the state level. *,**, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table A.2: ***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%.

Table A.3: *Predictability of Bank Runs Based on Fundamentals, Runs on Other Banks, and Macroeconomic Variables*

Dependent variable	Run without failure in $t+1$					
	(1)	(2)	(3)	(4)	(5)	(6)
Bank fundamentals:						
Surplus/Equity	-0.26**	-0.31**	-0.38**	-0.41***	-0.46**	-0.43**
	(0.12)	(0.15)	(0.16)	(0.14)	(0.17)	(0.17)
Noncore funding	7.11***	7.08***	6.16***	6.30***	6.11***	7.02***
	(1.96)	(1.81)	(1.97)	(2.10)	(1.97)	(2.01)
Surplus/Equity × Noncore funding	-5.35**	-7.14***	-5.89**	-4.75*	-5.27**	-6.60**
	(2.67)	(2.45)	(2.55)	(2.70)	(2.56)	(2.58)
Liquid Assets/Assets	-0.49**	-0.14	-0.62*	-0.60**	-0.59*	-0.17
	(0.23)	(0.14)	(0.33)	(0.28)	(0.34)	(0.15)
Deposits/Assets	0.68*	0.35*	0.23	0.50	0.42	0.47*
	(0.37)	(0.21)	(0.32)	(0.42)	(0.32)	(0.27)
Asset Growth (3 years)	-0.13	0.00	0.01	-0.08	-0.01	-0.03
	(0.12)	(0.06)	(0.08)	(0.10)	(0.07)	(0.08)
Macro conditions:						
NB failure rate			-1.17		-2.44	
			(4.40)		(4.26)	
NB run rate			0.71		8.53	
			(16.71)		(17.02)	
Stock market return			-0.61**			
			(0.25)			
Real GDP growth			0.33		0.09	
			(0.74)		(0.69)	
Local conditions:						
Run on other bank in same city				2.21***	2.19***	1.87***
				(0.73)	(0.73)	(0.60)
Local business failure rate				8.43***	2.03	2.13
				(2.70)	(5.29)	(6.33)
N	283417	283417	240691	237690	237690	237690
Mean dep. var	.3	.3	.33	.33	.33	.33
Year FE		✓				✓
AUC	0.674	0.822	0.725	0.747	0.754	0.824

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.

Table A.4: *Predictability of Bank Runs without Failure Based on Fundamentals, Runs on Other Banks, and Macroeconomic Variables*

Dependent variable	Run without failure in $t+1$					
	(1)	(2)	(3)	(4)	(5)	(6)
Bank fundamentals:						
Surplus/Equity	0.04	0.03	-0.02	-0.07	-0.07	-0.05
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.05)
Noncore funding	0.25	0.35	-0.22	-0.31	-0.32	0.09
	(0.51)	(0.48)	(0.60)	(0.61)	(0.62)	(0.50)
Surplus/Equity × Noncore funding	0.73	0.16	0.77	1.27	1.21	0.72
	(1.27)	(1.28)	(1.36)	(1.33)	(1.36)	(1.36)
Liquid Assets/Assets	-0.18	0.14***	-0.20	-0.22	-0.19	0.13***
	(0.16)	(0.05)	(0.21)	(0.18)	(0.21)	(0.04)
Deposits/Assets	0.14	0.09	-0.03	0.05	0.05	0.15
	(0.12)	(0.09)	(0.12)	(0.14)	(0.11)	(0.12)
Asset Growth (3 years)	0.04	0.09**	0.08*	0.06	0.07*	0.09*
	(0.04)	(0.04)	(0.05)	(0.05)	(0.04)	(0.05)
Macro conditions:						
NB failure rate			-0.08		-0.68	
			(1.76)		(1.61)	
NB run rate			2.10		5.29	
			(7.41)		(7.39)	
Stock market return			-0.25**			
			(0.11)			
Real GDP growth			0.41		0.32	
			(0.44)		(0.40)	
Local conditions:						
Run on other bank in same city				1.44***	1.43***	1.24***
				(0.48)	(0.48)	(0.40)
Local business failure rate				3.37***	2.61	3.29
				(1.15)	(2.41)	(2.99)
N	283417	283417	240691	237690	237690	237690
Mean dep. var	.14	.14	.16	.15	.15	.15
Year FE		✓				✓
AUC	0.577	0.810	0.670	0.679	0.713	0.817

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.

Table A.5: *Predictability of Failure Based on Fundamentals, Runs on Other Banks, and Macroeconomic Variables*

Dependent variable	Run without failure in $t+1$					
	(1)	(2)	(3)	(4)	(5)	(6)
Bank fundamentals:						
Surplus/Equity	-1.75***	-2.00***	-2.04***	-1.82***	-2.11***	-2.14***
	(0.53)	(0.61)	(0.68)	(0.56)	(0.75)	(0.70)
Noncore funding	70.95***	67.77***	71.02***	72.01***	70.75***	71.42***
	(18.16)	(16.64)	(18.19)	(19.55)	(18.52)	(18.27)
Surplus/Equity × Noncore funding	-95.81***	-102.26***	-106.36***	-101.31***	-104.96***	-106.71***
	(21.28)	(23.36)	(24.77)	(24.39)	(24.95)	(25.86)
Liquid Assets/Assets	-0.47	-2.05***	-1.58**	-1.09**	-1.63**	-2.15***
	(0.48)	(0.71)	(0.65)	(0.53)	(0.68)	(0.75)
Deposits/Assets	2.94**	1.18**	1.38*	2.48**	1.62*	1.23*
	(1.19)	(0.59)	(0.79)	(1.21)	(0.81)	(0.69)
Asset Growth (3 years)	-2.14***	-1.43***	-1.31**	-1.80**	-1.28**	-1.56**
	(0.80)	(0.53)	(0.60)	(0.76)	(0.61)	(0.62)
Macro conditions:						
NB failure rate			9.39		6.04	
			(12.24)		(14.21)	
NB run rate			-43.16		-15.33	
			(31.75)		(37.72)	
Stock market return			-1.94***			
			(0.60)			
Real GDP growth			-4.27*		-4.82*	
			(2.24)		(2.45)	
Local conditions:						
Run on other bank in same city				2.52***	2.44***	2.20***
				(0.77)	(0.69)	(0.65)
Local business failure rate				46.18***	8.81	1.74
				(6.66)	(15.47)	(15.56)
N	283417	283417	240691	237690	237690	237690
Mean dep. var	.81	.81	.91	.92	.92	.92
Year FE		✓				✓
AUC	0.868	0.896	0.892	0.890	0.896	0.906

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.

Table A.6: *Predictability of Failure with Bank Run Based on Fundamentals, Runs on Other Banks, and Macroeconomic Variables*

Dependent variable	Run without failure in $t+1$					
	(1)	(2)	(3)	(4)	(5)	(6)
Bank fundamentals:						
Surplus/Equity	-0.31***	-0.36***	-0.36***	-0.32***	-0.37**	-0.38***
	(0.10)	(0.12)	(0.13)	(0.10)	(0.14)	(0.14)
Noncore funding	7.61***	7.57***	7.36***	7.39***	7.25***	7.70***
	(1.86)	(1.77)	(1.88)	(2.01)	(1.88)	(1.98)
Surplus/Equity × Noncore funding	-6.66***	-7.91***	-7.51***	-6.67***	-7.09***	-7.85***
	(2.21)	(2.17)	(2.20)	(2.23)	(2.16)	(2.24)
Liquid Assets/Assets	-0.29***	-0.28*	-0.36**	-0.35***	-0.35**	-0.30*
	(0.10)	(0.16)	(0.14)	(0.13)	(0.15)	(0.17)
Deposits/Assets	0.50*	0.31**	0.28	0.42	0.35	0.28*
	(0.26)	(0.13)	(0.20)	(0.27)	(0.21)	(0.15)
Asset Growth (3 years)	-0.22*	-0.15*	-0.12	-0.17	-0.12	-0.16*
	(0.11)	(0.08)	(0.08)	(0.10)	(0.08)	(0.09)
Macro conditions:						
NB failure rate			-1.53		-2.13	
			(2.72)		(2.74)	
NB run rate			-0.02		4.58	
			(8.93)		(9.34)	
Stock market return			-0.33**			
			(0.15)			
Real GDP growth			-0.22		-0.33	
			(0.33)		(0.34)	
Local conditions:						
Run on other bank in same city				0.61***	0.60***	0.50**
				(0.23)	(0.22)	(0.20)
Local business failure rate				6.33***	0.96	0.22
				(2.20)	(3.13)	(3.41)
N	283417	283417	240691	237690	237690	237690
Mean dep. var	.15	.15	.16	.16	.16	.16
Year FE		✓				✓
AUC	0.813	0.876	0.848	0.858	0.862	0.887

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.

Table A.7: ***Bank Runs, Failures, and Fundamentals: Detailed Specifications***

Dependent variable	Failure in t+1							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Run	0.39***	0.56***	0.30***	0.25***	0.41***	0.33***	0.43***	0.43***
	(0.053)	(0.073)	(0.042)	(0.029)	(0.093)	(0.061)	(0.075)	(0.074)
Surplus/Equity		-0.024***				-0.0078***	-0.025***	-0.032**
		(0.0085)				(0.0018)	(0.0092)	(0.012)
Surplus/Equity × Run		-0.52***				-0.42***	-0.48***	-0.48***
		(0.12)				(0.10)	(0.089)	(0.089)
Noncore funding			0.37***			0.14***	0.37***	0.31***
			(0.11)			(0.038)	(0.11)	(0.084)
Noncore funding× Run			1.89***			1.95**	1.78***	1.77***
			(0.36)			(0.76)	(0.36)	(0.36)
OREO/Loans				0.10***		0.077***		
				(0.034)		(0.022)		
OREO/Loans× Run				2.05***		1.38**		
				(0.63)		(0.62)		
Liquid/Assets					-0.00043	0.0026	0.012	-0.022***
					(0.0063)	(0.0019)	(0.0076)	(0.0074)
Liquid/Assets × Run					-0.069	0.052	0.12	0.083
					(0.18)	(0.11)	(0.12)	(0.11)
Observations	265717	265717	265717	85208	265717	85207	265717	265717
R^2	0.060	0.066	0.097	0.11	0.060	0.13	0.10	0.12
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 A.8: ***Bank Runs, Failures, and Fundamentals: Different Time Periods***

Dependent variable	Failure in t+1					
	(1)	(2)	(3)	(4)	(5)	(6)
Run	0.43***	0.39***	0.92***	0.73***	0.44***	0.50**
	(0.074)	(0.080)	(0.15)	(0.053)	(0.081)	(0.19)
Surplus/Equity	-0.032**	-0.0067***	-0.024***	-0.14***	-0.016***	-0.084*
	(0.012)	(0.0015)	(0.0069)	(0.022)	(0.0051)	(0.037)
Surplus/Equity × Run	-0.48***	-0.51***	-0.79***	-0.31**	-0.59***	-0.27**
	(0.089)	(0.11)	(0.15)	(0.058)	(0.094)	(0.099)
Noncore funding	0.31***	0.12***	0.24***	0.72**	0.23***	0.88***
	(0.084)	(0.035)	(0.059)	(0.16)	(0.051)	(0.11)
Noncore funding× Run	1.77***	2.08***	0.76	0.77	1.70***	1.43
	(0.36)	(0.69)	(0.43)	(0.41)	(0.44)	(0.75)
Liquid/Assets	-0.022***	-0.00091	-0.014***	-0.056**	0.0026	0.047**
	(0.0074)	(0.0018)	(0.0035)	(0.015)	(0.0026)	(0.017)
Liquid/Assets × Run	0.083	-0.033	-0.78**	-0.49**	0.098	-0.13
	(0.11)	(0.16)	(0.29)	(0.090)	(0.14)	(0.26)
Observations	265717	131782	108585	25350	232591	33126
R^2	0.12	0.12	0.10	0.15	0.10	0.12
State FE	✓	✓	✓	✓		
Year FE	✓	✓	✓	✓		
Sample	1865-1934	1865-1913	1914-1928	1929-1934	No Crisis	Banking Crises

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

Table A.9: ***Role of Clearinghouses in the Pass-Through of Runs to Failure***

Dependent variable	Failure in t+1				
	(1)	(2)	(3)	(4)	(5)
Run	0.40***	0.28***	0.26***	0.37***	0.45***
	(0.047)	(0.030)	(0.037)	(0.040)	(0.090)
Clearinghouse City	-0.0025***	0.00029	0.00035	-0.0023**	-0.0064*
	(0.00091)	(0.00042)	(0.00051)	(0.00097)	(0.0038)
Clearinghouse City × Run	-0.089**	-0.070*	0.021	-0.11**	-0.072**
	(0.038)	(0.040)	(0.046)	(0.050)	(0.033)
Observations	275178	131782	74083	237279	37899
R^2	0.059	0.087	0.092	0.070	0.048
Mean dep. var.	0.0083	0.0030	0.0050	0.0049	0.029
Sample		<1914	Large Banks	No Crisis	Banking Crisis

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.

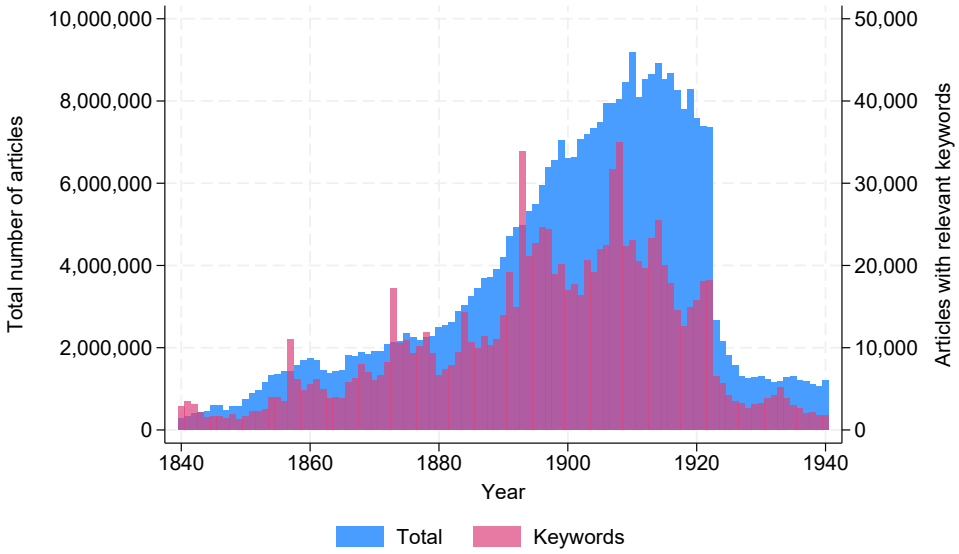
B Constructing the Bank Distress Episodes Dataset

Table B.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”

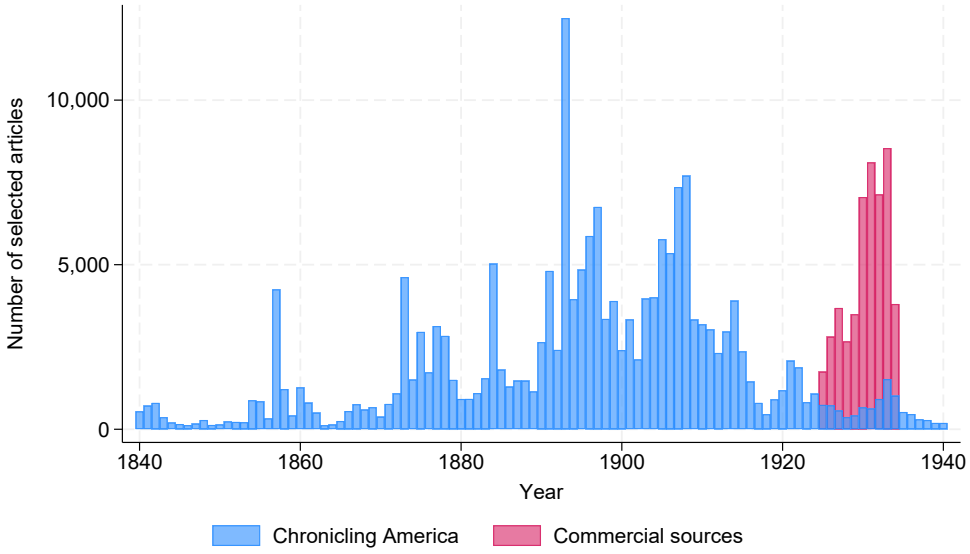
Notes: Matching is case-insensitive. To avoid false positives, unrelated words are first removed from the text before searching. These include geographical features (e.g., “river bank”, “snow bank”), proper names (e.g., “Albert Banks”), and common but unrelated financial terms (e.g., “bank loans,” “banknote”).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

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



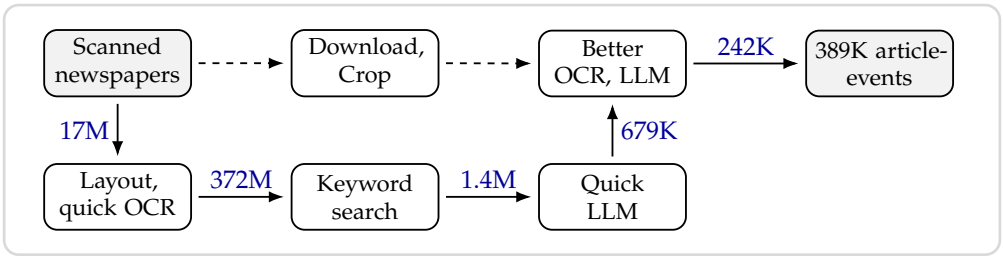
Notes: The left axis depicts total articles available per year in "Chronicling America", while the right axis shows the number of articles with keywords related to bank distress events (see Appendix Table B.1). The scale of the left axis is 200 times larger than that of the right axis. On average across 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 B.2: *Number Newspaper Articles Used in Final Sample*

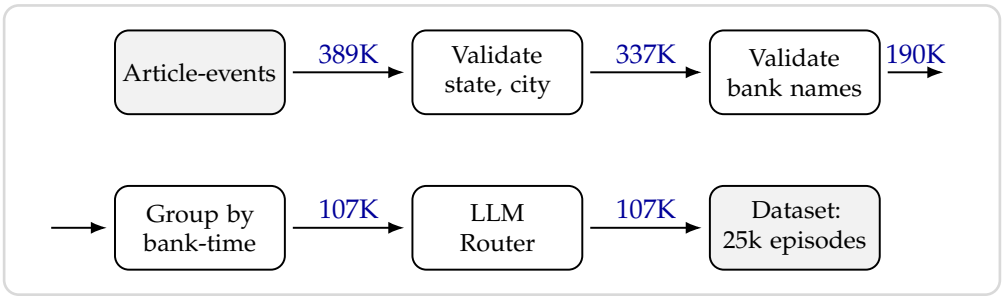


Notes: This figure shows the number of newspaper articles per year included in our final sample of newspaper articles. The two requirements for inclusion are i) having at least one keyword related to bank distress events (see Table B.1) and ii) being flagged by an LLM as related to a bank distress event (see Appendix B.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.

Figure B.3: *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.

B.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 B.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 B.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_name_unsure` (boolean): True if it is not clear which bank or city this event refers to.
- `bank_type` (string): The type of bank involved. Must be one of: "national", "state", "trust", "private", or "unknown". Use clues from the bank's name or the article to infer the type. For instance, names containing "National" indicate a national bank, "State" suggest a state bank, "Trust" indicate a trust company, etc. If uncertain, use 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, 1909-12-00 for an unknown day in December 1909.
  - `cause` (string): The classification of why the event took place. Only applicable for bank runs and bank suspensions (see below).
  - `cause_details` (string): Short description of the immediate cause or trigger of the run or suspension, expanding on the classification listed above. Only applicable for bank runs and bank suspensions.
  - `random_run` (boolean): For `event_type="run"` only. Set True only if the article explicitly describes a specific, discrete misinformation/communication mistake that triggered withdrawals and indicates it was false, mistaken, or later corrected (e.g., a misprint, erroneous telegram/wire report, hoax/prank, false announcement that the bank failed/closed, mistaken identity with another bank, or a clearly described misunderstanding that is corrected in the text). Set False otherwise (including when the article merely says "rumors", "nervousness", or "no cause", without describing a concrete misinformation event). If the run is described as driven by (i) adverse bank-specific information (embezzlement, bad loans, insolvency, scandals), (ii) failures/distress of other banks, (iii) macro/systemic panic, or (iv) local economic shocks, then `random_run` must be False even if the article uses reassuring language. When True, the `random_run_snippet` must include the phrase(s)
```

```
describing the misinformation/mistake and language indicating it was false/
corrected.
  - `random_run_snippet` (string|null): 5-15 words summarizing the
misinformation event (e.g., "false telegram reported bank had closed;
corrected same day"). Only if `random_run` is True.
  - `measures` (string): Actions undertaken by the bank as a response to a run
 (if any; only applicable for bank runs).
  - `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. To do so, follow this
decision rule:

1. First determine whether a run occurred at any point.
2. Then determine whether a suspension occurred.
3. Then determine whether the bank reopened or permanently closed.
4. Use this order to select the episode type.

These are the episode types:

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 agitated (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.
8. 'suspension_run_reopening': A bank suspends. As a consequence of the suspension, depositors run and/or are agitated (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.
9. 'other': Other type of event or sequence. Explain in the 'notes' field.


# Causes of bank runs and suspensions

1. 'rumor_or_misinformation': unfounded rumors or misinformation about the bank (false reports, misinterpreted events, malicious jokes, etc).
2. 'bank_specific_adverse_info': bank-specific adverse information affecting the solvency of the bank (embezzlement, suicides, discoveries of massive loans, or other scandals).
3. 'local_banks': information about runs and distress of other banks in the local economy
4. 'local_shock': information about the local economy that could affect the solvency of the bank (crop failures, default of local non-financial firms)
5. 'correspondent': failure or distress to correspondent banks or redemption agents.
6. 'macro_news': systemic financial panics, nationwide downturns, or other macroeconomic or political shocks (wars, currency crises, etc).
7. 'government_action': closed by government action (by receiver, examiner, banking holiday, etc). Only applicable for suspensions, not for bank runs.
8. 'voluntary_liquidation': voluntary liquidation and related events (charter expiration, etc). Only applicable for suspensions, not for bank runs.
9. 'other': other; unknown; or unable to tell.

# 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!
- The `cause` field should select one of the causes of bank runs when `event_type` is a run, and one of the causes of bank suspensions when `event_type` is a suspension.
- 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.

Lastly, follow this final check before answering:

- Does `episode_type` match the events listed?
- Are event types and causes consistent?
- Does the city/bank match the actual event location?

# Bank information

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

# Articles
```

```

The articles are listed below:

{articles}
```

Listing B.3: ***Final dataset—Main prompt.****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).*

```
You are an expert in historical U.S. banking events. Your task is to analyze
historical newspaper articles describing bank runs, and indicate which types
of measures the bank undertook in reaction to the bank run (to prevent the
bank run from becoming a bank failure).

Below will be a list of newspaper articles discussing a bank distress episode
that *should* include a bank run (plus other events such as suspensions,
receiverships, etc.) Please answer the following questions regarding the run.

# Questions

## General questions

- `success` (boolean): True if you were able to complete the task successfully
.
- `no_run_described` (boolean): Set to true if you believe there was no actual
 run described in the articles.
- `clearinghouse_involved` (boolean): Indicate if a clearinghouse was somehow
involved in the response. This can take place either through a loan, an
examination, or other measures.
- `who_ran_type` (string): The main type of depositors who were part of the
bank run (see below).

## Bank response measures

Indicate which of the following categories were undertaken by the bank. You
can report no categories, one category, or many categories.

- `accommodation` (boolean): Accommodated withdrawals, paid out depositors as
normal to prove solvency. Could also imply extending hours, opening early,
hiring extra tellers, delivering money to depositors' homes, etc.
- `clearinghouse_borrowing` (boolean): Borrowing from a clearinghouse.
- `borrowing` (boolean): Borrowing from other banks, a clearinghouse, large
institutions, or the Federal Reserve.
- `other_borrowing` (boolean): Borrowing from non-bank institutions, or from
```

```
the Federal Reserve.
- ‘public_signal‘ (boolean): Send signals to display the strength of the bank and its available resources, to reassure depositors. This includes physical delivery of gold, cash, etc. in a very public way (express wagons, train, airplanes, armored trucks, etc.). Often described as "truckloads of cash", emphasizing the visual effect. It can also include posting advertisements about the strength of the bank’s balance sheet, and paying depositors in a very public and visible way.
- ‘injection‘ (boolean): Equity injection or additional deposits by shareholders or other investors. Also includes mergers or takeovers, often involving additional capital.
- ‘partial_suspension‘ (boolean): Partial suspension of convertibility, either to some types of deposits (such as the invocation of the 30/60/90-day notice clauses for time deposits), or maximums per account (either in dollars or percentage).
- ‘full_suspension‘ (boolean): Full suspension of convertibility, where the bank stops paying all depositors, usually for a short period of time. Often described as the bank temporarily closing its doors, opening late, or closing early.
- ‘examination‘ (boolean): Bank books were examined by state supervisors, federal examiners (OCC, Federal Reserve), or by the local clearinghouse. The goal of this examination was to prove to depositors that the bank books were sound.
- ‘other‘ (string): Other types of measures; explain.


# Categories for ‘who_ran_type‘

If an article mentions multiple depositors, choose the items in this list that appear first:

1. ‘large‘: articles highlight a role for large depositors, businessmen, mercantile or commercial depositors, etc.
2. ‘institutional‘: articles mention institutional depositors, such as county or city treasurers, trust funds, federal, universities, etc.
3. ‘minorities‘: the articles highlight the role of immigrant groups, specific ethnicities (japanese, german, hungarian, italian, etc.), freedmen, or other demographic groups distinguishable from the general public.
4. ‘small‘: the articles highlight a role for small depositors or retail depositors
5. ‘workers‘: the articles highlight a role for specific professions such as farmers, miners, or factory workers.
6. ‘general‘: the article just mention the run was driven by the general
```

```
public or general depositors
7. 'unspecified': the articles only do not specify which type of depositors ran.


# Guidelines

- Only mark a category if the article describes the measure as a response to the bank run or depositor panic.
- If the article does not clearly describe a measure being undertaken, mark the category as false.
- You may mark zero, one, or multiple categories as true.
- Leave the 'other' empty unless there's a specific type of measure that does not fit any of the listed categories.


# Bank information

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


# Articles

The articles are listed below:

{articles}
```

Listing B.4: ***Final dataset—Bank response to run.*** *Prompt used to identify the types of measures undertaken by the bank as a response to the bank run, to prevent failure*

B.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[2]. 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.

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

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.

B.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.

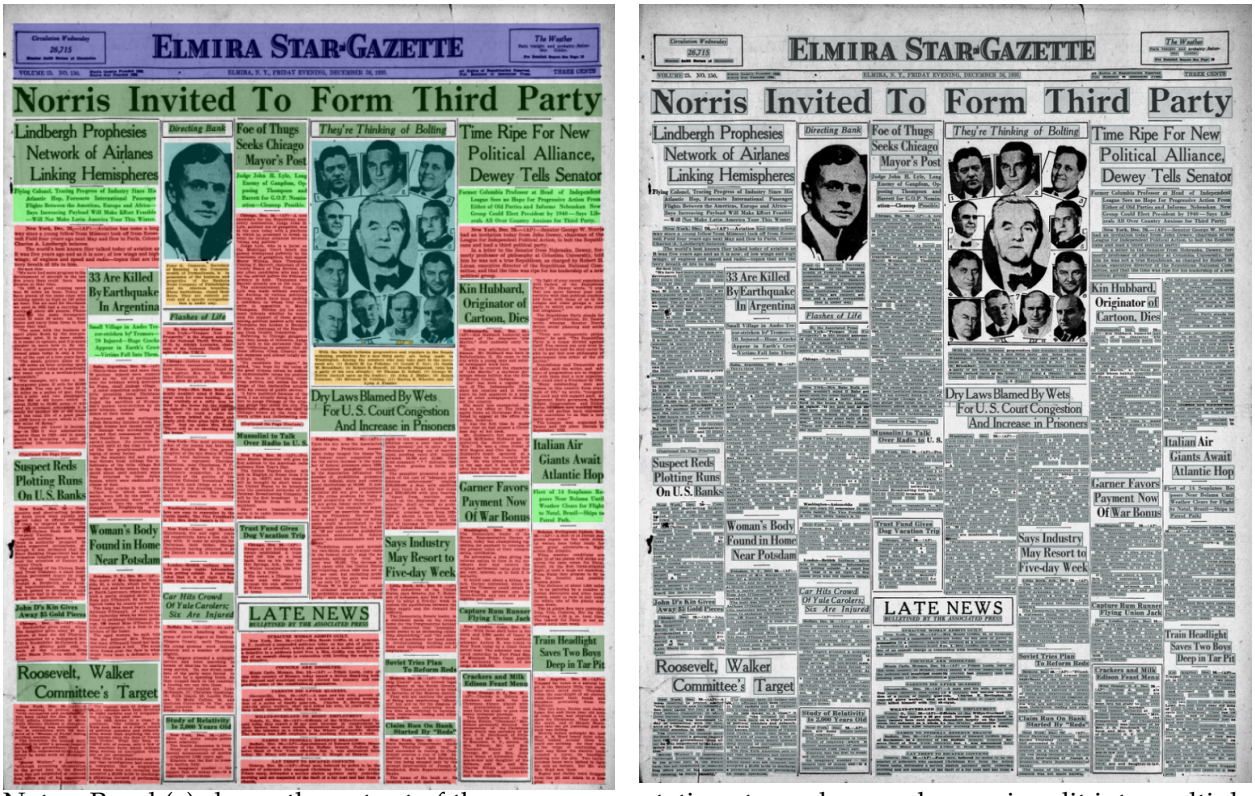
We use these datasets to create a validated list of U.S. banks, which are the main input to our `bank-census` Python package.

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.

B.4 Illustrative Examples of Newspaper Articles

Figure B.4: *Example of the layout and OCR steps*

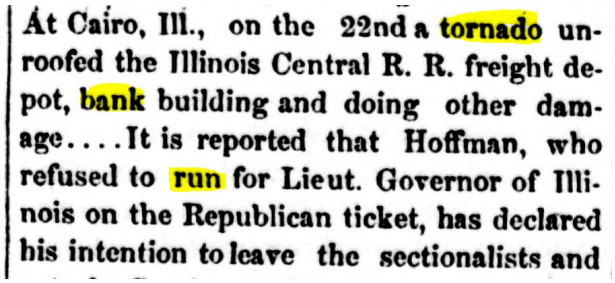
(a) ***Layout:*** *Page segmentation* **(b)** ***OCR:*** *Text extraction*



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).

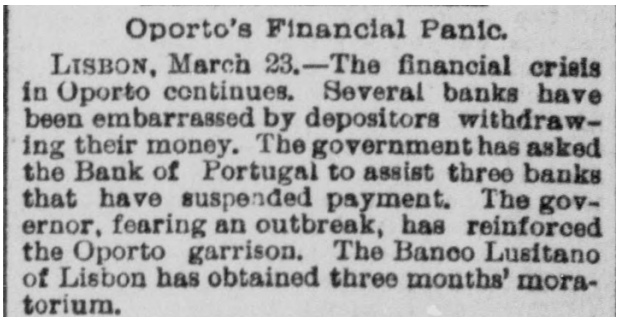
Figure B.5: *Examples of False Positives Flagged by Keywords and Excluded by LLMs*

(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

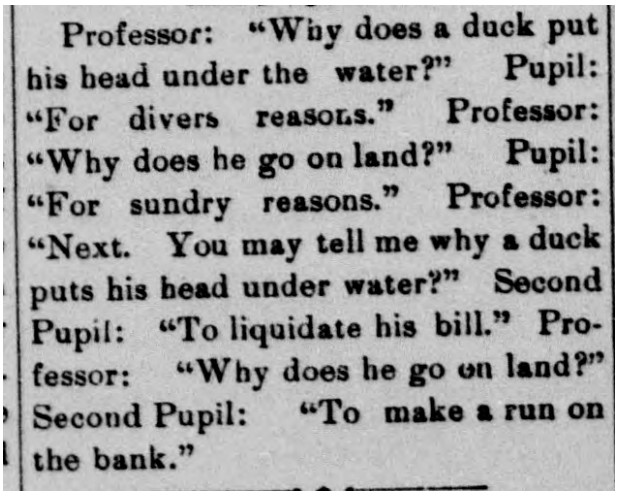
(b) *Foreign bank run*



Oporto's Financial Panic.

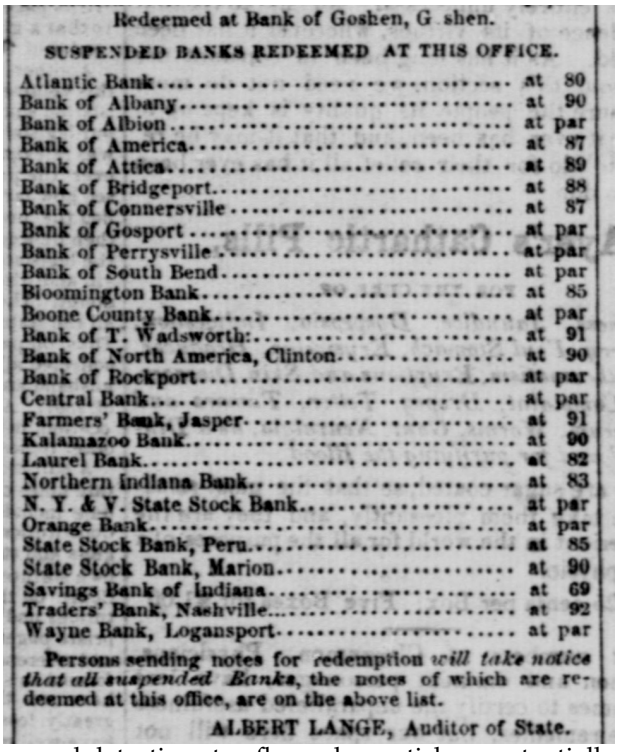
LISBON, March 23.—The financial crisis in Oporto continues. Several banks have been embarrassed by depositors withdrawing their money. The government has asked the Bank of Portugal to assist three banks that have suspended payment. The governor, fearing an outbreak, has reinforced the Oporto garrison.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

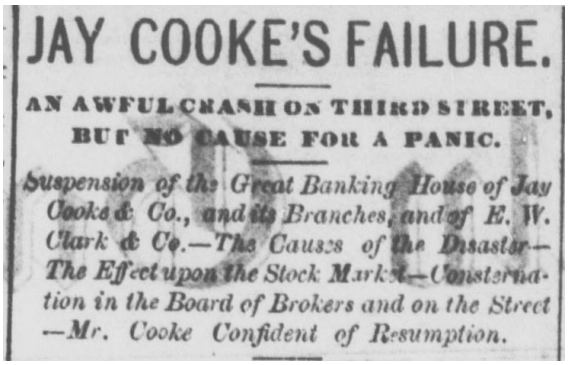
Persons sending notes for redemption *will take notice that all suspended Banks*, the notes of which are redeemed at this office, are on the above list.

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 B.6: *Examples of Articles Discussing Bank Runs or Suspensions*

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

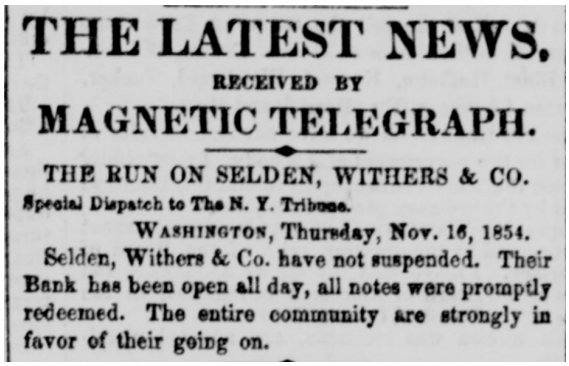


JAY COOKE'S FAILURE.

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.

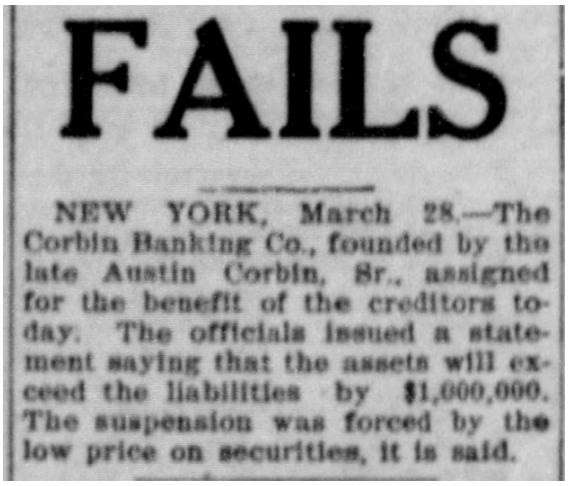
THE RUN ON SELDEN, WITHERS & CO.

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.

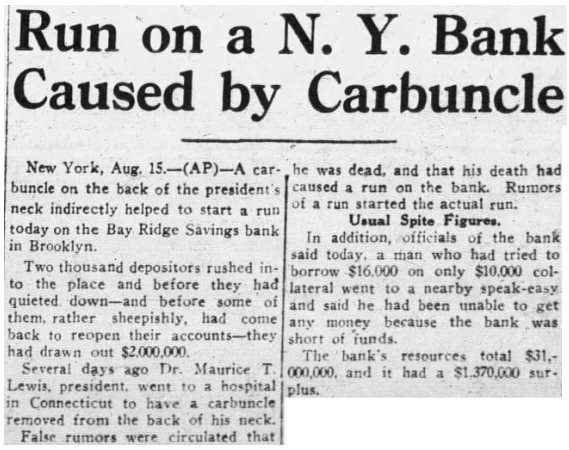
(c) *Bank failure (1907)*



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.

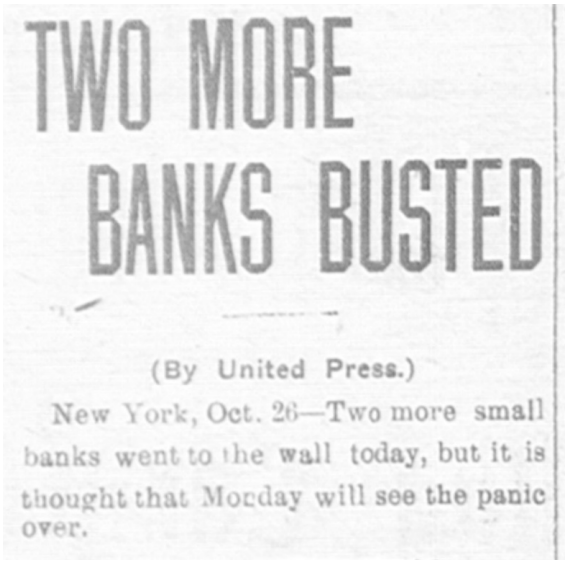
Several days ago Dr. Maurice T. Lewis, president, went to a hospital in Connecticut to have a carbuncle removed from the back of his neck. False rumors were circulated that he was dead, and that his death had caused a run on the bank. Rumors of a run started the actual run.

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.

Figure B.7: *Famous Bank Runs*

(a) *Bank of the US, December 1930*



Bank of the United States In New York Forced to Close; 58 Branches Are Affected

State Takes Possession of Assets and Announces Clearing House Member Banks Will Render Assistance In Form of Loans; Decision Follows All-Night Conference

New York, Dec. 11—Joseph A. Broderick, state superintendent of banks, today took possession of the Bank of the United States, a New York state institution, operating in New York city, with 58 branches scattered throughout greater New York.

A statement of September 24, 1930, gave the resources of the bank as $254,043,942 with deposits of $202,-972,469.

Supt Broderick announced that he had been informed that clearing house member banks will render assistance in the form of loans against the net claims of the depositors to the extent of 50 per cent of all claims properly authenticated. He issued the following statement:—

"The superintendent of banks, Joseph A. Broderick, today took possession of the business and property of the Bank of the United States, 535 Fifth avenue, New York city, pursuant of the provisions of section 57 of the banking law.

Heavy Withdrawals

"Mr Fred W. Piderit, at present an examiner in this department, has been appointed special deputy superintendent in charge.

"Negotiations with leading financial institutions of this city for the purpose of merger or reorganization having ended without result early this morning, the board of directors of the bank of the United States adopted the following resolution:—

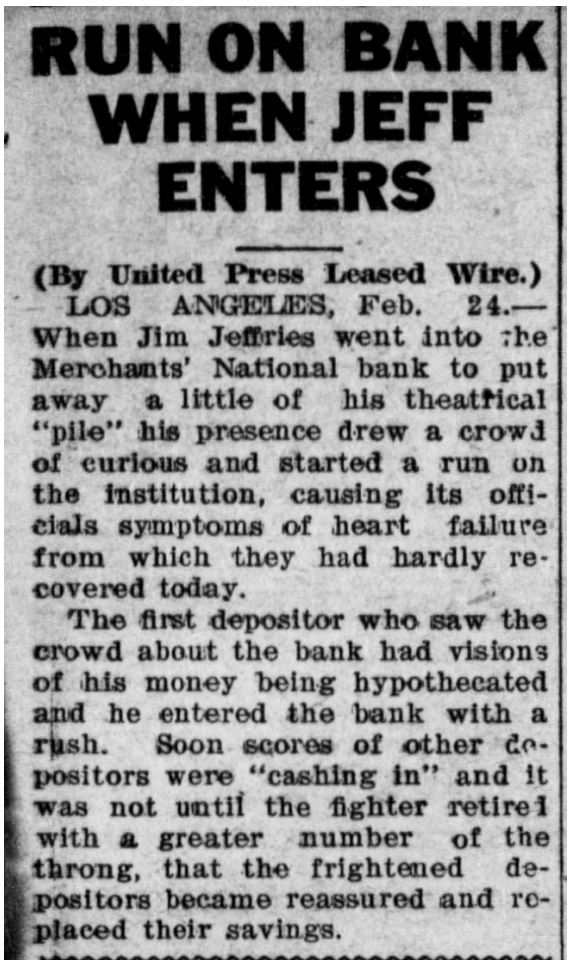
"'Resolved:—

"'That whereas rumors have been circulated which have caused abnormal withdrawals of deposits and it is feared that if the bank is opened Thursday morning these withdrawals may continue; that there will be in more than one of the branches of the bank large numbers of persons seeking withdrawals of their deposits which may result in disorder and it is desired that all depositors be treated equally and the assets conserved for their benefit; and whereas the directors feel that in view of conditions it would be unwise to continue to receive and pay out moneys, that the officers of the bank and they are hereby authorized to advise the superintendent of banks of the state of New

Continued on Page Twenty

Figure B.8: *Examples of Articles Illustrating Runs Exemplifying Various Theories*

(a) *Asymmetric information run: Presence of famous boxer draws crowd, leading to a run out of incorrect concerns that crowd a signal of insolvency (Merchants' National Bank, February 24, 1910)*



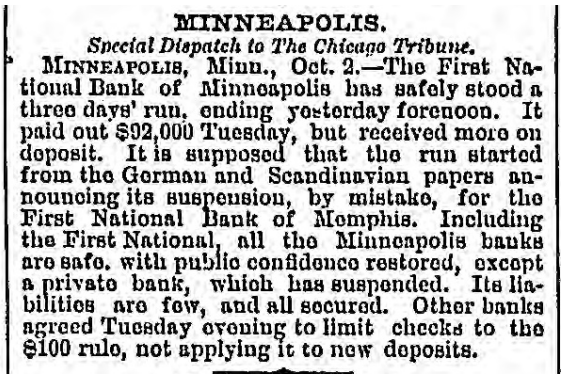
RUN ON BANK WHEN JEFF ENTERS

(By United Press Leased Wire.)

LOS ANGELES, Feb. 24.—When Jim Jeffries went into the Merchants' National bank to put away a little of his theatrical "pile" his presence drew a crowd of curious and started a run on the institution, causing its officials symptoms of heart failure from which they had hardly recovered today.

The first depositor who saw the crowd about the bank had visions of his money being hypothecated and he entered the bank with a rush. Soon scores of other depositors were "cashing in" and it was not until the fighter retired with a greater number of the throng, that the frightened depositors became reassured and replaced their savings.

(b) *Non-fundamental run: Run based on false rumor in newspaper (First National Bank Minneapolis, October 1, 1873)*

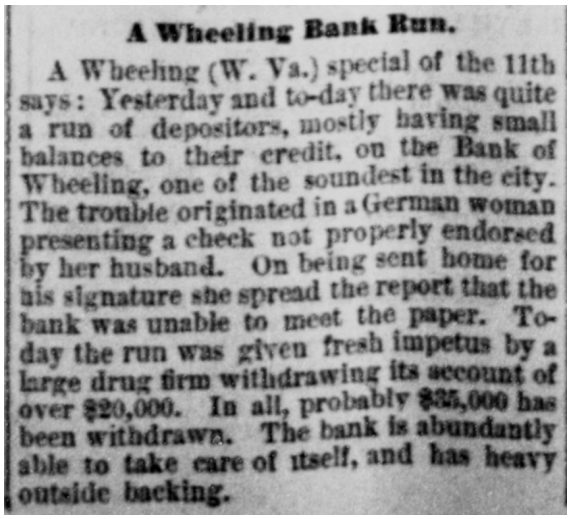


MINNEAPOLIS.

Special Dispatch to The Chicago Tribune.

MINNEAPOLIS, Minn., Oct. 2.—The First National Bank of Minneapolis has safely stood a three days' run, ending yesterday forenoon. It paid out $92,000 Tuesday, but received more on deposit. It is supposed that the run started from the German and Scandinavian papers announcing its suspension, by mistake, for the First National Bank of Memphis. Including the First National, all the Minneapolis banks are safe, with public confidence restored, except a private bank, which has suspended. Its liabilities are few, and all secured. Other banks agreed Tuesday evening to limit checks to the $100 rule, not applying it to new deposits.

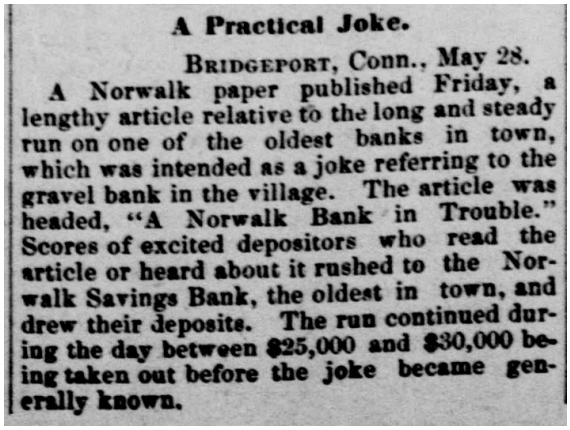
(c) *Non-fundamental run: Run based on false rumor by depositor (Bank of Wheeling, March 11, 1884)*



A Wheeling Bank Run.

A Wheeling (W. Va.) special of the 11th says: Yesterday and to-day there was quite a run of depositors, mostly having small balances to their credit, on the Bank of Wheeling, one of the soundest in the city. The trouble originated in a German woman presenting a check not properly endorsed by her husband. On being sent home for his signature she spread the report that the bank was unable to meet the paper. To-day the run was given fresh impetus by a large drug firm withdrawing its account of over $20,000. In all, probably $35,000 has been withdrawn. The bank is abundantly able to take care of itself, and has heavy outside backing.

(d) *Non-fundamental run: Run based on joke article misinterpreted by excited depositors (Norwalk Savings Bank, May 26, 1884)*



A Practical Joke.

BRIDGEPORT, Conn., May 28.

A Norwalk paper published Friday, a lengthy article relative to the long and steady run on one of the oldest banks in town, which was intended as a joke referring to the gravel bank in the village. The article was headed, "A Norwalk Bank in Trouble." Scores of excited depositors who read the article or heard about it rushed to the Norwalk Savings Bank, the oldest in town, and drew their deposits. The run continued during the day between $25,000 and $30,000 being taken out before the joke became generally known.