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 of bank runs in the United States from 1863 to 1934. Applying large language models to historical newspapers, we identify 3,421 runs on individual banks. The resulting series aligns closely with narrative chronologies of U.S. banking crises and provides rich new micro-level information on runs. Runs are considerably more likely in weak banks but also occur in strong banks, especially in response to negative news about the real economy or the broader banking system. However, runs typically result in failure only for banks with poor fundamentals. Strong banks survive runs through various mechanisms, including interbank cooperation and suspension of convertibility. At the local level, runs on banks with poor fundamentals translate into substantially larger declines in deposits, lending, and manufacturing activity than runs on strong banks. Our findings imply that poor fundamentals are central to explaining both when runs occur and when they have severe economic effects, tempering the view that small shocks can generate discontinuous jumps to bad equilibria through self-fulfilling run dynamics.

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1 Introduction

Bank runs are a salient feature of many financial crises. While it is well understood that financing illiquid assets with demandable liabilities makes banks vulnerable to a sudden withdrawal of funding (Diamond and Dybvig, 1983), the role of runs in financial crises remains controversial. Runs can be seen as the key turning point, whereby even small shocks can generate severe crises with widespread bank failures. Alternatively, runs can be viewed as a consequence of deeper fundamental problems in the financial system, exacerbating crises rather than being their primary cause.

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? And when do runs produce severe real economic contractions?

A key challenge for understanding the causes and consequences of runs is the absence of systematic microdata on the occurrence of bank runs. 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, Puri and Ufier, 2023; Correia, Luck and Verner, 2025). 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; Cipriani, Eisenbach and Kovner, 2024) or consider aggregate data on banking panics (Calomiris and Gorton, 1991; Baron, Verner and Xiong, 2021; Jamilov et al., 2024).

We overcome this gap by studying the near-universe of runs in the U.S. banking system from 1863 to 1934 as recorded in contemporary newspapers. Our approach leverages advances in large language models and the digital accessibility of historical newspaper articles (Dell et al., 2023). This allows us to construct a novel database that identifies 3,421 runs on individual banks in newspaper accounts during 1863–1934. We also identify 13,069 bank suspensions and 10,330 failures. Each event we identify is backed by newspaper accounts, which we publicly document at finhist.com/bank-runs. Our approach allows us to study bank runs that result in failure, runs that result in temporary suspension but not failure, and runs that have no further consequences. We combine these data on bank runs with information on bank balance sheets, data on macroeconomic conditions, and newly digitized data on local business failures and manufacturing activity.

We provide three main findings. First, runs are considerably more likely in weak

banks, but can also occur in strong banks. Second, runs typically only result in failure for banks with weak fundamentals. Third, runs on weak banks lead to substantially larger local declines in deposits, lending, and manufacturing activity than runs on strong banks. Taken together, our findings suggest that poor fundamentals 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 are less common 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 and banking crises (e.g., Sprague, 1910; Friedman and Schwartz, 1963; Bernanke, 1983; Calomiris and Gorton, 1991; Wicker, 2006; Richardson, 2007), though this work has largely relied on aggregate data or episode-specific analysis of narrative evidence. Our paper, in contrast, combines both comprehensive narrative accounts and exhaustive bank-level microdata.

We start by validating our novel bank run database. Spikes in the rate of bank runs recorded in newspapers line up closely with existing narrative chronologies of banking crises in the United States (Jalil, 2015; Baron, Verner and Xiong, 2021), both at the aggregate and regional level. For national banks, the annual unconditional probability of a run is 0.36%. This number rises to 1.5% during crisis years. Moreover, national bank failures for which newspapers recorded a bank run involve a 4 percentage points larger deposit outflow right before failure than those without mention of a run. For banks that survive bank runs, we also find large deposit declines in their annual public financial statement around the event.

With these novel data on runs, 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. We establish that 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, Luck and Verner, 2025). We document that runs are considerably more likely in poorly-capitalized banks, banks with less liquid

assets, and banks that rely relatively more on noncore funding.

While runs are more likely in banks with weak fundamentals, the ability to predict runs with fundamentals alone is somewhat low—especially compared to the predictability of bank failures. However, the incidence of runs is well explained when combining information on bank fundamentals with information on the local and national economic and banking conditions. For instance, we find that 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 especially help explain runs on healthier banks.

Second, when do bank runs result in bank failure? We find that a bank's annual probability of failure increases by 37 percentage points when subject to a run. This is a large effect, given that the annual unconditional probability of bank failure is 0.85%. However, it also implies that a run is not a death sentence. There are more runs without bank failure than runs with failure, highlighting a key novel insight from our approach.

We further establish that whether a run results in failure depends crucially on a bank's financial health. Runs are significantly more likely to result in failure for banks with weak fundamentals. Conditional on a run, a bank with very weak fundamentals—defined as being in the lowest decile of our preferred metric that summarizes a bank's financial health—has a 63% probability of failing. In contrast, we cannot statistically reject that the *ex ante* strongest banks, measured as being in the top decile of the same metric, never fail when subject to a run. Thus, weak bank fundamentals are necessary for a run to be associated with bank failure.

To better understand how banks with sound fundamentals are able to survive runs, we leverage additional context provided in newspaper articles. We find that newspapers often report that surviving banks accommodate withdrawals and attempt to signal strength to depositors. A common signal of strength 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 a common way to successfully resolve runs, often alongside bank examination to signal solvency to depositors, consistent with Gorton (1985a). In 10% of runs, newspapers mention that the local bank clearinghouse is involved by providing liquidity or conducting an examination.

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, the finding that runs happen predominantly in weak banks supports the notion that fundamentals are important (Morris and Shin, 2000; Goldstein and Pauzner, 2005). Second, the fact that even healthy banks can be subject to runs following adverse news shocks

is 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; Dang, Gorton and Holmström, 2020). Finally, the fact that both weak and strong banks can be subject to a run even though they can be separated based on simple public balance sheet metrics suggests that depositors are at times inattentive. The predictability of both runs and failures suggests that depositors tend to be sleepy and are slow in responding to weak bank fundamentals. However, the importance of news shocks suggests that salient information can cause depositors to wake up and run.

In line with this interpretation, we further find that 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.

We also explicitly examine the scope for non-fundamental runs to trigger failure (Diamond and Dybvig, 1983). We define non-fundamental runs as those that, according to the newspapers, are caused by misinformation or depositor confusion and are not related to bank or economic conditions. Using textual analysis, we identify a sample of 44 non-fundamental runs on national banks. This exercise also provides sharper identification by zooming in on a set of runs that are relatively random and thus free of confounding factors. The probability of failure following a non-fundamental run is 11%, substantially 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. While strong fundamentals reduce the probability of failure after a run generally, this is especially true for non-fundamental runs for which only banks with the weakest fundamentals fail. This pattern casts doubt on a strong form of the view that liquidity problems alone can trigger severe financial distress.

Third, what are the economic consequences of bank runs with and without failure? At the bank level, we find that 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 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.

Finally, we study the consequences of bank runs for local city-level deposits, lending, and manufacturing activity. We first show that runs lead to only modest local declines in deposits, lending, and manufacturing activity when they occur in *ex ante* strong banks, but significantly larger effects when they occur in weak banks. Non-fundamental runs entail no significant adverse local effects. Further, we use the richness of our bank distress episodes data to consider the city-level consequences of runs *without* failure versus runs *with* failure. We find that spikes in the local rate of runs *without* failure lead to modest declines in deposits and loans at the city level and no effect on manufacturing activity. In contrast, runs with failure lead to more severe contractions in local deposits, credit, and manufacturing activity.

Taken together, our findings have two broad implications. First, while runs can occur in both weak and strong banks, poor fundamentals are necessary for runs to result in bank failures. Second, failures, and their corresponding weak fundamentals, are a key mechanism for banking sector distress to translate into substantial contractions in credit and real activity. 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. These patterns, in turn, temper the view that small shocks can result in large jumps to bad equilibria via self-fulfilling runs on demandable debt. Rather, bank runs seem to only be associated with major economic distress when they take place in the context—and typically as a consequence—of already weak fundamentals. At the same time, because even insolvent banks can remain liquid for some time, a run may be an important determinant for the timing and economic costs of bank distress.

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 3,000 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 and real activity. 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, Eisenbach and Kovner (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 can withstand 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; Iyer, Puri and Ryan, 2016; Blickle, Brunnermeier and Luck, 2024; Jamilov et al., 2026). Moreover, existing work suggests that interbank and wholesale markets may be crucial for how runs play out (Afonso, Kovner and Schoar, 2011; Perignon, Thesmar and Vuillemey, 2018; Mitchener and Richardson, 2019). Finally, Richardson and Troost (2009) also show that central bank interventions can be important in influencing bank survival rates during times of heightened financial distress.

Our paper also relates to studies of banking panics using aggregate or regional data. Gorton (1988), Calomiris and Gorton (1991), Alston, Grove and Wheelock (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, Verner and Xiong (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 large literature on understanding bank failures (e.g., White, 1984; Calomiris and Mason, 2003; Correia, Luck and Verner, 2025). These studies find that failed banks displayed weak balance sheets before failure and argue that runs usually accelerated the failure of already insolvent banks, rather than causing widespread collapse of otherwise solvent institutions; see Correia, Luck and Verner (2026) and references therein for a comprehensive review. Our paper makes a distinct contribution to this literature by expanding the scope of bank distress to systematically include runs and suspensions without 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 bank failures and the resulting 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, Hilt and Zhou (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 provides an innovation to the narrative approach to identification in macroeconomics and finance (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, Schularick and Taylor, 2013; Baron, Verner and Xiong, 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 have been insurmountable without a squadron of researchers. Furthermore, the narrative approach to classifying banking crises involves researcher judgment, leading to some disagreement about which episodes constitute widespread bank runs (e.g., Jalil, 2015; Baron, Verner and Xiong, 2021; Hoon et al., 2025). Our newspaper-based approach provides a systematic method to resolve 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. Section 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 estimates the consequences of runs for affected banks and for local deposits, lending, and manufacturing activity. 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 discuss the predicted real economic consequences of bank runs with and without failure.

Our emphasis on bank failure as a 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" because it mitigates informational and agency frictions through relationship-based screening and monitoring. When a bank fails, this informational capital is destroyed, leading to persistent reductions in credit. As a result, bank failure provides a natural mechanism through which runs 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

To fix ideas, we outline the empirical predictions from theories of runs with a simple model. Consider a bank that lives for two periods, $t \in \{1, 2\}$. The bank holds liquid cash C and illiquid loans L. Assets are financed by deposits D and equity E. There is a continuum of risk-neutral depositors, each holding one unit of deposits. Deposits are demandable at $t = 1$. However, the bank lacks the liquid funds to pay all depositors in the initial period, $D > C$. In $t = 2$, the loan portfolio pays off θL. We refer to the gross return θ as the fundamental of the economy. There is no discounting, deposits pay zero interest, and the return on cash is zero.

At time $t = 1$, depositors observe θ and decide whether to keep their deposits in the bank or withdraw. Depositors who keep their deposits in the bank until $t = 2$ receive a convenience benefit of c per unit of deposit. We denote the total amount of withdrawals w. If $w > C$, the bank is illiquid, and it is forced into failure (receivership). In failure, the loan portfolio value is reduced to $(1 - \rho)\theta L$. The reduction in value ρ can reflect that the receiver is less skilled at managing bank assets than the banker or a fire sale discount. We assume sequential service of withdrawals. Depositors who withdraw while the bank is liquid receive full repayment, whereas depositors remaining in the bank in failure receive a pro-rata share of the remaining assets.

The bank is fundamentally insolvent when the fundamental is sufficiently low that it cannot fully repay depositors, $\theta < \theta^S \equiv \frac{D-C}{L}$. However, the bank may be subject to a run that renders it illiquid and forces it into failure if $\theta < \theta^L \equiv \frac{D-C}{(1-\rho)L}$. The threshold for run-induced failure exceeds the solvency threshold, $\theta^L > \theta^S$. Thus, for $\theta \in [\theta^S, \theta^L)$, a self-fulfilling run constitutes an equilibrium. Because depositors are served on a first-come, first-served basis, they 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 forcing it into

value-destroying failure.

Thus, the bank is exposed to the possibility of a self-fulfilling panic run that is not strongly tied to bank or broader economic fundamentals. We refer to these as *non-fundamental runs* (Diamond and Dybvig, 1983).[1] Non-fundamental runs can occur in relatively healthy banks and following a small shock that brings the fundamental θ just below θ^L. These runs are thus unpredictable jumps to a bad equilibrium that are not necessarily linked to particularly weak fundamentals.

Models of non-fundamental runs do not predict a sharp relation between fundamentals and runs. However, runs may be more likely following bad realizations of fundamentals. Models of *fundamental-based panic runs* capture this idea (Morris and Shin, 2000; Goldstein and Pauzner, 2005).[2] 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 private signal of the bank's asset value θ. This global games set-up can feature a unique equilibrium as a function of fundamentals. A bank run occurs when bank fundamentals θ fall below a specific threshold $\theta^* \in (\theta^S, \theta^L)$. However, importantly, the model generates panic runs, in the sense that, absent the run, the bank would have been solvent and survived for $\theta \in [\theta^S, \theta^*)$.[3] Runs thus amplify bad fundamentals. The empirical prediction is that fundamentals-based panic runs should occur in banks with weak fundamentals.[4]

In another class of theories, runs are modeled 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). In particular, suppose at time $t = 1$ depositors receive a noisy public signal $y = \theta + \epsilon$, where ϵ is a mean-zero shock. In this setting, if a signal is sufficiently bad, $y < \overline{y}$, a run constitutes an equilibrium. For example, depositors might run in response to a signal that a recession is imminent (Gorton, 1988; Calomiris and

[1] 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.

[2] See also Allen and Gale (1998) and Rochet and Vives (2004) for models where runs occur after the realization of poor fundamentals. To capture the idea that runs should occur in relatively weaker banks, Ennis and Keister (2003) and Gertler and Kiyotaki (2015) assume that non-fundamental runs are more likely in banks with lower θ.

[3] In practice, depositors may be 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, Luck and Verner, 2025).

[4] 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, 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 even in response to small shocks (Gorton, 2012; Gorton and Ordoñez, 2014).[5]

Information-based theories also capture the idea that depositors can misinterpret public signals and mistakenly run on healthy banks. If the realization of the shock ϵ is sufficiently low, then a bank with a high $\theta > \theta^L$ can be run. Depositors can react to a range of signals. 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).[6] The bank run in the film *Mary Poppins* is an evocative example. Runs on other banks may lead depositors to revise their beliefs 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 suggested by the original connotation of "panic." Information-based theories predict that panics should occur in response to adverse public signals, leading to runs on both weak and strong banks.

Prediction 1. ***Causes of bank runs.*** *Non-fundamental runs can happen both in banks with weak and strong fundamentals. Fundamental-based panics happen in weak banks. Information-based runs are more likely in weak banks, but can also happen in strong banks 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.[7]

[5] In recent work by Dang, Gorton and Holmström (2020), runs arise when an adverse signal about the collateral backing 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.

[6] 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.

[7] 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 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 allow for runs without failure. Several mechanisms can prevent the failure of a solvent bank 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. For instance, 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 a 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.[8]

In our simple framework, suppose that if $w > C$, the bank can choose one of two actions. Either it can enter failure, where assets are liquidated at $(1-\rho)\theta L$, as above. Instead, it can suspend and pay a proportional cost τ to have its books examined and certify that it is solvent. Supposing that the cost of examination is lower than of failure, $\tau < \rho$, the bank chooses to temporarily suspend and pay the cost τ if $\theta > \theta^{Susp} \equiv \frac{D-C}{(1-\tau)L}$, where $\theta^{Susp} \in (\theta^S, \theta^L)$. Thus, if depositors see an overly negative public signal of fundamentals, but true fundamentals are relatively strong, $\theta \geq \theta^{Susp}$, then the bank is subject to a run and suspends, thereby avoiding failure. A mechanism such as suspension thus reduces the set of solvent banks that can be pushed into failure by a run.

Prediction 2. ***Bank runs and failures.*** *In canonical non-fundamental and fundamental-based run models, run equilibria typically imply failure. In information-based models, runs can occur on solvent banks and need not end in failure when mechanisms such as suspension or interbank support are available.*

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 the run itself is a key

[8]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.

discontinuous turning point whereby a small shock can translate into high economic costs through bank failures and credit contraction. This view plays a key role in prominent accounts of the Great Depression and Great Recession (Friedman and Schwartz, 1963; Gorton, 2012; Bernanke, 2018). Theories of non-fundamental runs and fundamental-based panic runs most directly embody this mechanism (Diamond and Dybvig, 1983; Goldstein and Pauzner, 2005). Information-based theories also allow runs to lead to discontinuous jumps, but the consequences of runs depend more on underlying fundamentals and on whether banks can survive the run.

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 (Admati and Hellwig, 2014; Gennaioli and Shleifer, 2018; Baron, Verner and Xiong, 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 empirical implications. On the one hand, if runs themselves are key turning points and the primary cause of distress, then runs should unconditionally be associated with severe outcomes, irrespective of a bank's initial fundamentals.[9] On the other hand, if runs themselves are not the root cause of distress, runs should only be associated with severe consequences when they result in failure. In that case, runs should result in bank failure and large economic contractions when they occur in banks with weak fundamentals, but they should be less costly for banks with sound fundamentals.

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).[10] Again, in cases where banks

[9]Of course, observing severe outcomes after runs does not imply that the run was the *cause* of these outcomes, so this is a necessary but not sufficient condition.

[10]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).

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.***

(a) If runs themselves are key turning points and the primary cause of distress, then runs should typically be associated with severe outcomes, irrespective of initial bank fundamentals.

(b) If runs are symptoms or amplifiers of deeper fundamental banking sector distress, they should result in severe economic consequences when they occur in banks with weak fundamentals, but be less costly if they occur in banks with sound fundamentals.

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 an episode in which a substantial number of depositors suddenly demand that their bank or banks convert claims into cash or the liabilities of another bank.

We also collect newspaper mentions of other key bank events: suspensions and failures. Our definition of a suspension includes both temporary and permanent closure of a bank (i.e., it fails to open its doors) as well as partial suspension of convertibility. The latter case includes episodes when a bank limits deposit withdrawals to a maximum amount per depositor or suspends withdrawal of less liquid deposits, such as time deposits. We define failures as suspensions that become permanent.[11] 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*

[11] In rare cases, banks are placed in receivership but restored to solvency later. We nonetheless classify these cases as failures.

Stories dataset from Dell et al. (2023) to separate pages into articles.[12] 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.[13] Figure B.2 shows the number of articles used in our final analysis across time and source.

Methodology We produce our dataset of bank distress events in two stages. The procedure is summarized in Figure 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.[14] 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 is 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 assume some degree of knowledge from earlier articles.

[12] *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.

[13] The number of articles in *American Stories* 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).

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

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[15] and write a Python package that flexibly matches bank names while being robust to typos and variations on how these 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.[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 into the 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

[15]This list augments those of Weber (2006), Jaremski and Fishback (2018), and Correia, Luck and Verner (2025), with additional banks manually compiled for this paper, based on *Rand McNally Bankers Directory* (multiple years), *Trust Companies of the United States* (multiple years), and other sources.

[16]Appendix B.3 discusses this package in more detail.

[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.

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.

Note that by construction a bank must suspend before or at failure. Thus, any failure will also be a suspension. 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, Luck and Verner (2025).

Measurement Issues We note three measurement issues that are important to keep in mind when using information on bank distress recorded in newspapers. 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.

Humans vs LLMs To test the accuracy of our data construction pipeline, we independently hired eight undergraduate students for one month to search newspapers.com using our keywords for runs across our full sample period. This produced a database of 228 runs with valid bank and city names. Of these 228 runs, our approach identified 216, for a match rate of 95%. Among national banks, our approach only fails to identify one run. This highlights that our approach identifies nearly all recorded runs. Extrapolating linearly, a heroic assumption, constructing such a database through hand collection would require about 10,000 human hours, in addition to the untold cost of dissuading a group of promising research assistants from becoming economists. Below in Section 4, when presenting our database, we discuss additional tests to validate the quality of the data.

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, Luck and Verner (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, Luck and Verner (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, Luck and Verner (2025). Given that information on bank fundamentals and closures is consistently available only for national banks, much of our analysis focuses on the sample of national banks.

To capture local defaults of non-financial firms that can trigger bank asset losses, we create a novel 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,

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

we scale non-financial business failures by the number of manufacturing establishments from the census. To proxy real economic activity at the city level, we also create an index of manufacturing activity from *Bradstreet's* Trade at a Glance tables (1917-33) and descriptions of Business Conditions (1933-35). The index is consistently available every week for 30 cities from 1917 through 1933 and every month from 1933 to 1935. Appendix C provides additional details and shows that the index is highly correlated with aggregate industrial production. Finally, we use information on the banking crisis years and the month of banking panics from Baron, Verner and Xiong (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. Besides providing basic descriptive statistics, we also 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. As noted above, 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 3,421 bank run episodes. The majority of runs do not involve failure. We find 1,906 runs without failure and 1,515 runs with failure. We also find 13,069 episodes involving a suspension, and 10,330 episodes involving a failure.[20] Thus, the majority of distress episodes recorded in newspapers involve a bank failure.

Panel (b) in Table 1 shows the unconditional probability of bank distress episodes in our 1863-1934 panel of national banks. 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. Such precise records

[20] As noted above, a bank always suspends before or at failure. Hence, by definition, there are no failures without suspensions.

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	3421	1325	581	1515	10330	13358
No crisis	1769	744	227	798	6420	7495
Banking crisis	1652	581	354	717	3927	5880
1863-1913 (NB Era)	1816	933	312	571	3975	5124
1914-1928 (Early Fed)	603	196	89	318	2484	2898
1929-March 6, 1933	954	186	167	601	2874	3586
After March 6, 1933	48	10	13	25	997	1750

Panel B: Number of events as a share of total number of banks (in %), national banks

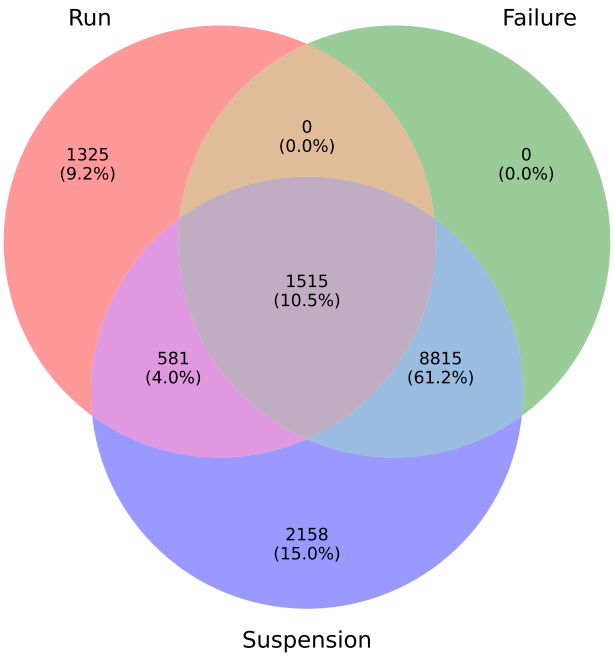
Sample	Bank run				Failure	Suspension
	All	Run w/o suspension	Run with sus. + reopen.	Run with failure		
All	.364	.157	.0648	.143	.72	.984
No crisis	.205	.0907	.0252	.0893	.431	.52
Banking crisis	1.54	.647	.352	.545	2.87	4.4
1863-1913 (NB Era)	.379	.18	.0794	.12	.308	.533
1914-1928 (Early Fed)	.163	.0749	.0127	.0759	.614	.646
1929-March 6, 1933	1.16	.314	.103	.751	3.9	4.11
After March 6, 1933	.242	.0291	.0775	.145	6.15	9.54

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, Luck and Verner (2025). Both panels 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, Verner and Xiong (2021).

are not available for state banks.[21] A national bank's annual unconditional probability of failing between 1864 and 1934 is 0.72%, while the unconditional probability of being subject to a run is 0.36%. Over the same time, national banks also face a 0.22% probability

[21]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.

Figure 1: *Bank Run, Suspension, and Failure Episodes*



Notes: The sample is all bank distress episodes involving a run, suspension, and/or bank failure over the period 1863-1934 for all bank types. By definition, failure requires suspension, so there are no cases with failure but without suspension.

of being subject to a bank run without failing. About 30% of runs without failure involve suspension.

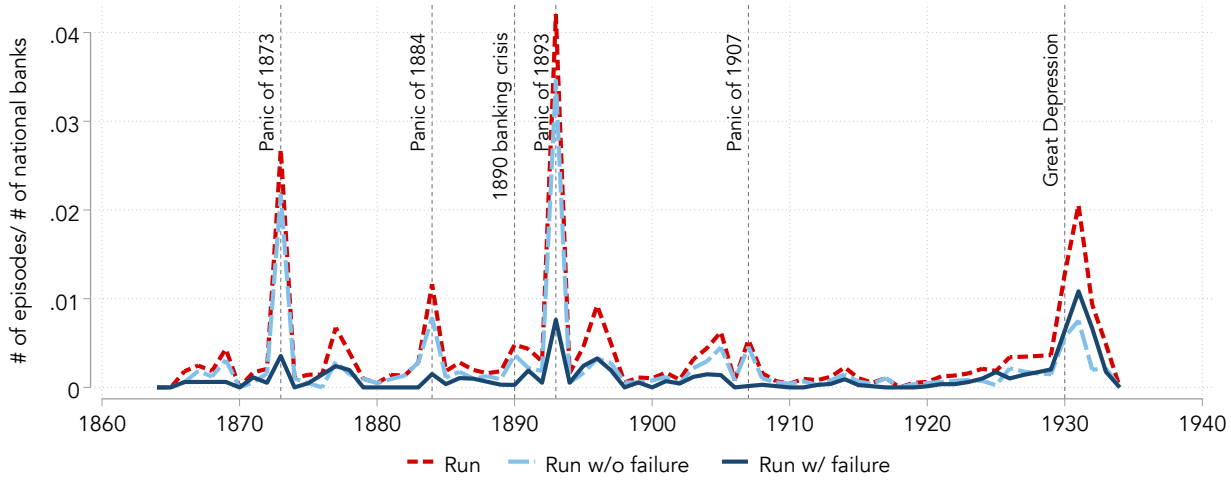
4.2 Bank Runs During and Outside of Narrative Banking Crises

Figure 2 presents the rate of runs in the time series by plotting the number of runs as a fraction of the total number of banks in each year.[22] We again focus on national banks so that we can calculate rates relative to the total number of banks. The rate of runs spikes 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 also distinguishes between bank runs with and without failure. Runs without

[22]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, Richardson and Vossmeyer, 2023). This is explained by the fact that newspapers may not have seen a need to report individual bank suspensions right around the time the entire banking system suspended.

Figure 2: ***Bank 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, Luck and Verner (2025). The figure also separates runs into runs without failure and runs with failure.

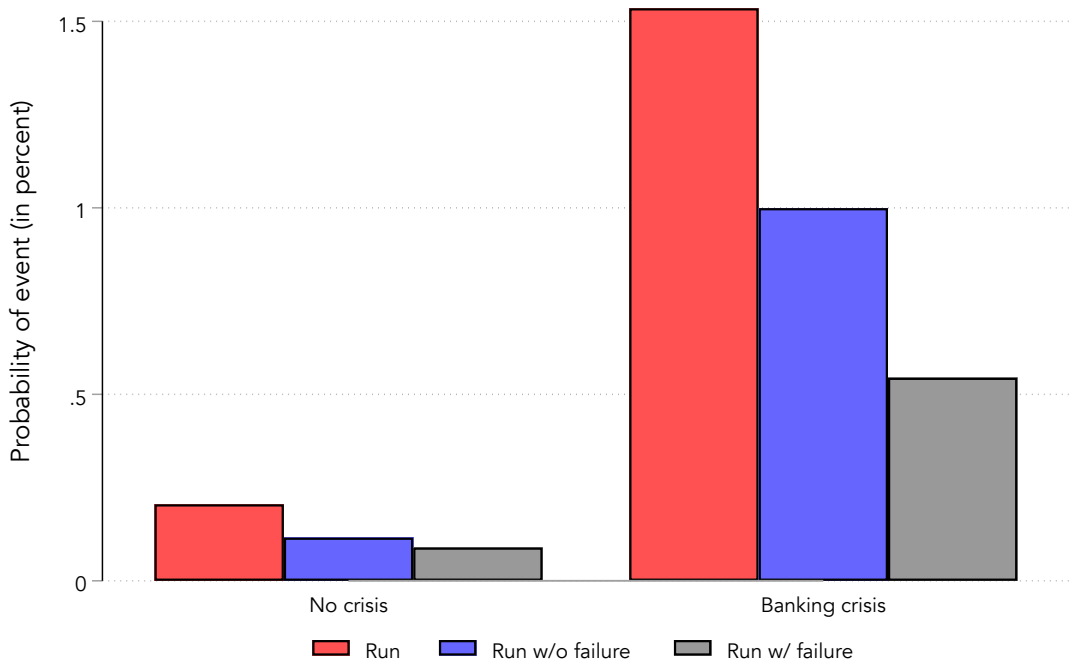
failure are especially pronounced during major banking crises, especially the "panics" of the national banking era. For example, the Panic of 1893 featured a particularly large number of runs without failure (but with temporary suspensions), as noted by previous work (e.g., Carlson, 2005). Runs with failure spiked during the Panic of 1893 and the Great Depression. Interestingly, most failures do not involve discussions of runs. Failures without runs were elevated during the 1890s and 1920s agricultural downturn, see Appendix Figure A.1.

In the time series, runs appear much more likely during major banking crises. Figure 3 plots the rate of runs during and outside of banking crisis years and confirms this finding. Crisis years are based on the narrative chronology by Baron, Verner and Xiong (2021).[23] The probability of a run increases by roughly a factor of eight during banking crisis years compared to other years. The probability of a national bank being subject to a run is around 0.2% outside of banking crisis years but increases to more than 1.5% during a crisis; see also panel (b) of Table 1. The probability of a failure increases from 0.43% to 2.9%, and the probability of a suspension from 0.52% to 4.4%.

We confirm that bank runs and other distress events recorded in newspapers 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 in a regression framework. Specifically, Table 2 examines whether our list of bank distress events lines up with the

[23]Baron, Verner and Xiong (2021) define panics as episodes of severe and sudden withdrawals of funding by bank creditors from a significant part of the banking system.

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, Verner and Xiong (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.

narrative banking crisis dates from Jalil (2015) and Baron, Verner and Xiong (2021).[24] With this narrative information, we estimate the following regression at the state-month level:

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

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 defined as in Baron, Verner and

[24]Jalil (2015) provides information on state-level banking panics. Jalil (2015) also reports city-level panics, which we aggregate to the state level. Baron, Verner and Xiong (2021), as noted above, provide years of the onset of banking crises and the starting month of major banking panics.

Xiong (2021). Regional banking panic$_{st}$ is a dummy that takes the value one if a state is subject to a banking panic according to Jalil (2015) in a given month. We compute Driscoll and Kraay (1998) standard errors with a bandwidth of three years.

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 run events per state per month. During years with a banking crisis, the number of runs in a state-month more than doubles, increasing by 0.49 on average.

Moreover, bank run spikes also line up remarkably well with the month of banking panics from narrative accounts. During panic months, the number of runs increases by another 1.5. This result is also confirmed by Figure A.2 in the Appendix, which 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, Verner and Xiong (2021). During the National Banking Era, newspapers also pick up several additional borderline cases of banking panics, such as 1896. For the Great Depression, we capture the various waves of runs discussed in narrative accounts. In particular, we capture the rise in runs in late 1930, the rise in runs from March to August 1931, the spike in runs after the U.K. leaves gold in September 1931, and another rise from the end of 1932 to the banking holiday in May 1933, consistent with the aggregate narrative of Friedman and Schwartz (1963). We also capture a small spike in runs in early 1930 and during the Chicago panic in the summer of 1932 (Calomiris and Mason, 1997). Further, while bank runs were more likely before the banking holiday of 1933, failures and suspensions were mostly reported during or after the banking holiday, in line with Jaremski, Richardson and Vossmeyer (2023).

Table 2 further shows that during months of non-major regional banking crises identified by Jalil (2015), the number of runs increases by 4.85. 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 18 during the Florida "Fruit Fly Panic" in July 1929 (Carlson, Mitchener and Richardson, 2011).

Taken together, this evidence indicates that our database of runs lines up quantitatively with existing qualitative narrative chronologies of banking crises at the aggregate and regional level.

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	0.46***	0.72***	1.35***
	(0.058)	(0.16)	(0.19)
Major banking panic month	1.53**	-0.70***	1.23*
	(0.70)	(0.18)	(0.62)
Regional banking panic	4.85***	1.66***	5.08***
	(0.89)	(0.41)	(1.47)
N	10790	10790	10790
Mean dep. var.	0.36	0.80	1.01

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 panic months are taken from Baron, Verner and Xiong (2021) and regional banking crises between 1863 and 1929 are from Jalil (2015). Table A.1 presents estimates separately including a dummy for each regional crisis. The sample period is 1863-1934. Driscoll and Kraay (1998) standard errors in parentheses with a bandwidth of three years. *,**, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

4.3 Additional Data Quality Checks

To further validate the value of our novel bank distress data, we perform several additional basic data quality checks.

First, we correlate the true failure rate for national banks based on official OCC receiverships with the failure rate according to our classification from newspapers. The aim of this exercise is to assess how informative newspapers are about bank distress events whose occurrence we can verify with certainty. 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. 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 informative about important bank distress events.

Second, we study whether actual deposit outflows are higher around bank runs

recorded in newspapers. Figure A.5c 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 4 percentage points larger deposit outflow before failure. This finding provides evidence that narrative accounts of runs in newspapers indeed capture many failures with large deposit outflows.

The previous exercise focuses on deposit outflows conditional on bank failure. As a third exercise, Figure A.5d plots the probability of a bank distress episode as a function of annual deposit growth conditional on survival. Bank runs and suspensions that do not result in 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.

Finally, Figure A.5e 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, in line with events for larger banks being more newsworthy. Thus, the incidence of bank runs is more likely to be under-reported for smaller banks. To address this potential shortcoming of our data, we show below that our main findings are robust to using only the largest banks.

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 start by assessing the likelihood of a bank run as a function of bank-specific and broader economic conditions. As discussed in Section 2, theories of bank runs have different predictions for what can explain the incidence of runs. Theories of non-fundamental runs (e.g., Diamond and Dybvig, 1983) suggest that even healthy banks can be subject to

a run, thus reducing the explanatory power of bank fundamentals. In contrast, theories of fundamental-based panic runs (e.g., Goldstein and Pauzner, 2005) suggest that runs should predominantly happen in banks with weak fundamentals. Finally, theories of information-based runs (e.g., Gorton, 1988) suggest that runs are more likely after adverse public signals about the state of the banking sector or the macroeconomy.

Motivated by these predictions, we examine the ability of various sets of variables to capture an elevated risk of runs and 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, for which we have information on both bank runs and bank-level fundamentals.

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, 1984; Calomiris and Mason, 1997; Correia, Luck and Verner, 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 explain bank runs and other bank distress episodes. To assess the explanatory power, we calculate the in-sample 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 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 (see, e.g., Richardson, 2007), 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

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	-0.21			-0.43**
	(0.13)			(0.19)
Noncore funding	7.83***			6.93**
	(2.57)			(2.66)
Surplus/Equity × Noncore funding	-5.31**			-5.76**
	(2.57)			(2.66)
Liquid Assets/Assets	-0.54**			-0.62*
	(0.25)			(0.34)
Deposits/Assets	0.72*			0.40
	(0.39)			(0.33)
Asset Growth (3 years)	-0.13			-0.01
	(0.13)			(0.09)
Macro conditions:				
NB failure rate		-1.91		-1.15
		(3.91)		(4.23)
NB run rate		10.26		1.16
		(16.93)		(16.51)
Business failure rate		17.09		19.09
		(13.53)		(14.19)
Real GDP growth		0.60		0.17
		(0.88)		(0.74)
Stock market return		-0.62**		-0.57**
		(0.28)		(0.25)
Local conditions:				
Run on other bank in same city			2.89***	2.81***
			(0.89)	(0.91)
Local business failure rate			12.12***	-0.13
			(4.11)	(5.52)
N	286382	277105	273490	239863
Mean dep. var	.33	.36	.35	.35

Notes: This table presents estimates of Equation (2). Driscoll and Kraay (1998) standard errors in parentheses with a bandwidth of three years to allow for residual correlation within and across banks in proximate years. *,**, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

are more likely following years with low stock returns. They are also more likely when business failures are high, although the relation 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: ***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	0.678	0.819	0.722	0.744	0.749	0.821
Panel B: Bank run without failure						
AUC	0.582	0.813	0.663	0.667	0.708	0.815
Panel C: Bank run with failure						
AUC	0.814	0.871	0.850	0.864	0.868	0.888
Panel D: Bank failure						
AUC	0.868	0.896	0.892	0.891	0.897	0.907
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.2 (for Panel A), Table A.3 (for Panel B), Table A.4 (for Panel C), and Table A.5 (for Panel D).

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 0.68.

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 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 conditions. 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 with an AUC of 87% (panel D).

Column (2) shows that including year fixed effects substantially increases the AUC 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 leads to a substantial increase in the AUC for bank runs without failure, from 58% to 71%. However, it leads to a more moderate 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. This is in line with banking panics occurring after bad news about the economy or the banking system, 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, Luck and Verner (2025). Thus, fundamentals-based theories are promising for explaining bank runs and failures, while information-based theories are important for explaining runs without failure.

6 Bank Runs and Bank Failure

We next investigate the relation between 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.

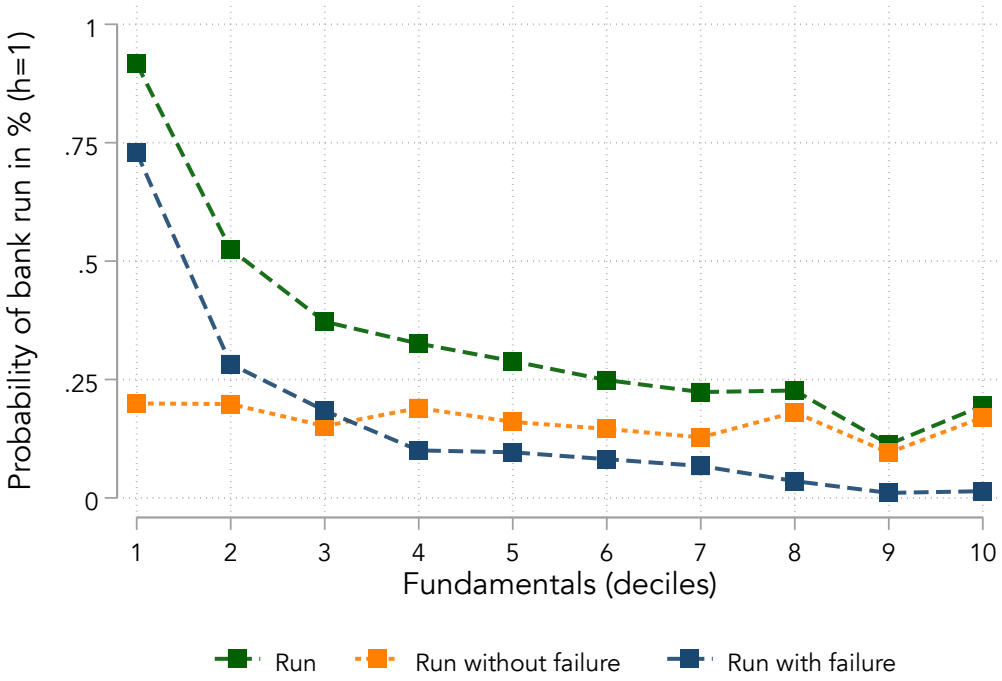
6.1 Bank Runs and Failure across Weak and Strong Banks

Summarizing Fundamentals We start by constructing a simple bank-level measure of fundamentals, denoted 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.

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. In line with the patterns documented in Table 3, 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 in a given year. However, while much less likely, strong banks can be subject to runs. The probability drops for weaker banks, but only to about 20 basis points for banks with the strongest fundamentals. Nevertheless, while the probability of a run is higher for weak banks, the level and difference relative to strong banks is still relatively low in absolute terms, in line with the relatively modest predictability of runs based on fundamentals alone Table 4.

Figure 4 further plots the probability of runs with and without failure across the distribution of bank fundamentals. The figure reveals two distinctive patterns. Runs that do not result in failure are only weakly related to fundamentals (see the yellow line). These runs are almost equally likely to happen in both weak and strong banks. Runs with

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



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

failure, in contrast, 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. A bank that is above the 7th decile of the fundamentals distribution will very rarely be subject to a run and fail. Hence, a look at the relationship of runs, failures, and fundamentals in the raw data suggests that 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 To study the importance of bank fundamentals for whether a bank can withstand a run or not more formally, we estimate 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)	(2)	(3)	(4)	(5)	(6)
Run	0.37***	0.25***	0.42***	0.39***	0.36***	0.30***
	(0.056)	(0.042)	(0.055)	(0.055)	(0.052)	(0.054)
Fundamentals		-3.47***				
		(0.75)				
Fundamentals × run		-12.4***				
		(2.01)				
Strong fundamentals			-0.0100**		-0.0059**	
			(0.0040)		(0.0028)	
Strong fundamentals × run			-0.34***		-0.31***	
			(0.046)		(0.045)	
Very strong fundamentals				-0.0074**		-0.0036**
				(0.0031)		(0.0018)
Very strong fundamentals × run				-0.35***		-0.27***
				(0.066)		(0.062)
Observations	268483	268483	268483	268483	72500	72500
Mean dep. var.	0.0085	0.0085	0.0085	0.0085	0.0051	0.0051
Sample					Large Banks	Large Banks

Notes: This table presents estimates of Equation (3). We define a bank to have "strong" fundamentals when $\text{Fundamentals}_{bt-1}$ is in the upper tercile of the historical distribution. "Very strong fundamentals" indicates when $\text{Fundamentals}_{bt-1}$ is in the highest decile. Driscoll and Kraay (1998) standard errors in parentheses with a bandwidth of three years to allow for residual correlation within and across banks in proximate years. *,**, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table 5 presents the results from estimating Equation (3) for the sample of national banks from 1863 to 1934. Column 1 shows that the probability of bank failure increases by 37 percentage points when a bank is subject to a bank run, roughly in line with Figure 1. This increase in the probability of failure is considerable given that the unconditional probability of failure is 0.85% in this sample. Thus, a bank subject to a run is more than 40 times more likely to fail than the average bank, and runs often result in failure. At the same time, a run is not a death sentence, and runs without failure are more common than runs with failure.

Column 2 in Table 5 further shows that banks with strong fundamentals have a significantly lower probability of failure, echoing the findings in Correia, Luck and

Verner (2025). Moreover, in line with the evidence from Figure 4, the negative coefficient on $\text{Fundamentals}_{bt-1} \times \text{Run}_{bt}$ implies that strong fundamentals significantly reduce the probability of bank failure after a run.

In order to quantify how fundamentals matter for whether a bank fails after a run, we further interact the run indicator with an indicator for whether a bank's fundamentals are "strong." We define a bank as having "strong" fundamentals when $\text{Fundamentals}_{bt-1}$ is in the upper tercile of its historical distribution. Column 3 shows that banks in the two bottom terciles of the fundamentals distribution have a 42 percentage points higher chance of failing when subject to a run, but banks with strong fundamentals have a 34 percentage points lower probability of failure. Thus, having strong observable fundamentals substantially reduces the probability of failure when a bank is exposed to a run. Column 4 further shows that banks with very strong fundamentals, defined as being in the top decile of $\text{Fundamentals}_{bt-1}$, have a 35 percentage points lower probability of failure compared to all other banks, which have a 39% chance of failing in this specification. Thus, very strong banks rarely fail when subject to a run. While the fact that very strong banks can be subject to runs is in line with both theories of non-fundamental runs and information-based runs (Prediction 1), the fact that strong banks do not fail after a run is only predicted by theories of information-based bank runs (Prediction 2).

Figure 5 presents a visualization of the likelihood that a run leads to failure across the full distribution of bank fundamentals. For each decile d of $\text{Fundamentals}_{bt-1}$, we estimate

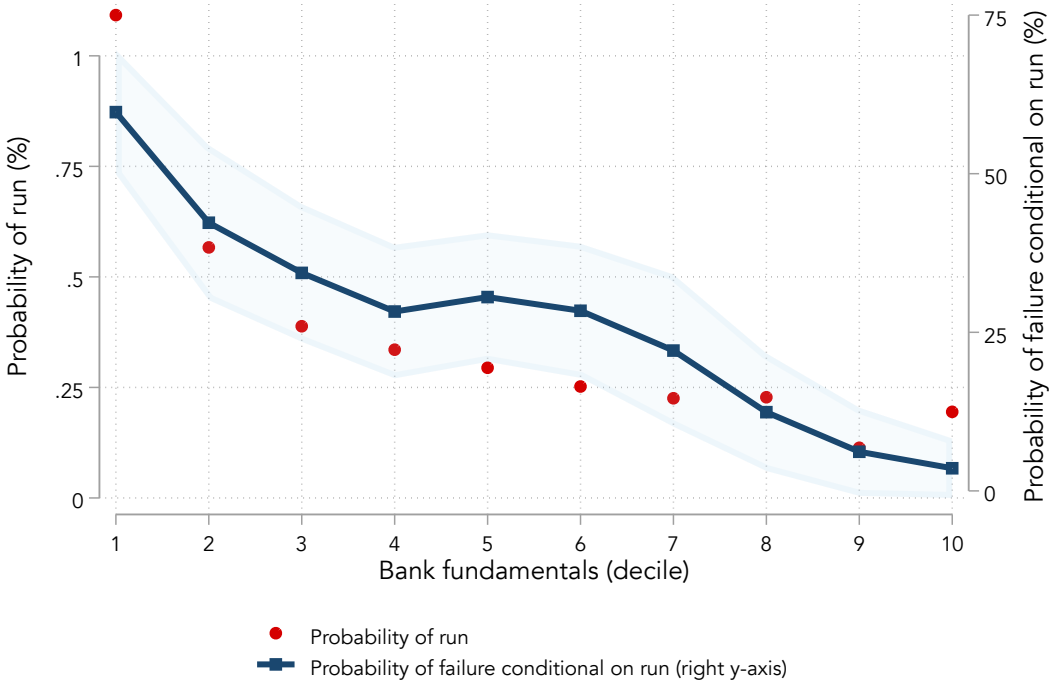
$$\text{Failure}_{bt} = \beta_0^d + \beta_1^d \text{Run}_{bt} + \epsilon_{bt}, \quad d = 1, ..., 10, \tag{4}$$

and plot the estimated coefficients $\{\hat{\beta}_1^d\}$. The figure shows that runs are associated with a 62% 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 4% and is not statistically significant. Thus, we cannot reject that runs on the healthiest banks never cause bank failures. Overall, our evidence suggests that bank-specific fundamentals are central to understanding the pass-through of bank runs to failure.

Before proceeding, we note that these estimates provide upper bounds on the likelihood that a run causes a healthy bank to fail. The reason is that $\text{Fundamentals}_{b,t-1}$ may, in some cases, be an imprecise proxy of bank health. For instance, publicly available financial statements cannot capture episodes where a bank was insolvent but had not yet

recognized losses (e.g., due to an unexpected shock, fraud, or hidden losses). 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.[25]

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 with a bandwidth of three years to allow for residual correlation within and across banks in proximate years.

High Frequency Dynamics Figure 6 zooms in on the daily dynamics of the probability of failure around a run. The figure reports the cumulative probability of bank suspensions and bank failure around a run for all national banks from estimating local projections of the form:

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

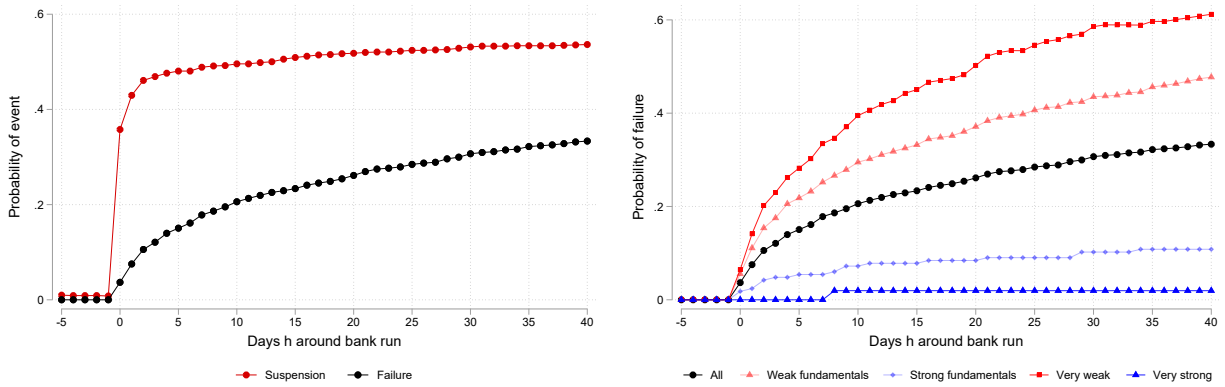
[25]Correia, Luck and Verner (2025) document that failed national banks had both low recovery rates and low asset quality according to OCC bank examiners. That study argues this suggests that the vast majority of failed banks were fundamentally insolvent, unless one assumes large value destruction from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

Figure 6 panel (a) plots the cumulative probability of bank suspension and bank failure following a run. We find that the probability of bank failure rises gradually to almost 37% in the 40 days following a run. Thus, essentially all failures following a run happen roughly within a month of the run. The dynamics of suspension display two differences compared to the dynamics of failure. First, suspension is more likely than failure, occurring more than 50% 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) further visualizes the cumulative probability of bank failure following a run across banks that report different fundamentals before the run. 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 Fundamentals$_{bt-1}$, measured as of the most recent call report. In line with the evidence in Table 5, we find a striking difference in the likelihood of bank failure across weak and strong banks following a bank run. Very weak banks see a relative quick spike in failures after runs and a cumulative probability of failure of over 60% within the 40 days following a run. In contrast, the probability of failure is close to zero for very strong banks.

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

(a) *Suspensions and bank failures around bank runs* **(b)** *Bank failure around runs by bank fundamentals*



Notes: Both panels plot coefficients from estimating Equation (5). In panel (a), we report results with failure and suspension as the outcome variables. In panel (b), we estimate the responses separately based on bank fundamentals, measured with Fundamentals$_{bt-1}$. Specifically, we define bank fundamentals categories as: "very weak" (bottom decile), "weak" (bottom tercile), "strong" (top tercile), and very strong (top decile) .

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 five years before failure and are on a worse trajectory of deteriorating fundamentals in the years before failure. 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. Moreover, we also compare banks that fail with a run to banks that fail without a narrative indication of a run. We find that banks that fail without a run are slightly worse across a range of fundamentals compared to banks that fail with a run, but the differences are modest. This suggests that runs may accelerate the failure of banks with deteriorating banks and trigger the failure of marginally healthier banks. However, given that these banks are on very similar trajectories, many failures with runs were likely inevitable.

Robustness As noted above, 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, possibly leading to an upward-biased estimate of the likelihood that a run results in failure for small banks. To address this concern, it is useful to verify that our findings hold in the sample of larger banks. Column 5 of Table 5 zooms in on large banks, defined as banks in the top quartile of total assets. In the sample of large banks, we find that banks have a 36% higher chance of failing when subject to a run, but banks with strong fundamentals have a 31 percentage points lower probability of failure. In column 6, we consider the effect of runs on failure for very strong banks and find that the chance of failure is 27 percentage points lower compared to a 30% higher chance of failure for other banks. Thus, for large banks, strong fundamentals provide (nearly) fully insulate a bank from the risk of failure in response to a run.

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

6.2 Bank Responses to Runs

Banks with strong fundamentals typically do not fail when subject to a run. This raises the following questions: How do banks respond to runs? Why are strong banks able to withstand runs? What measures do banks take to fend off runs? To answer these questions, we exploit additional information in newspapers. We identify 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 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,

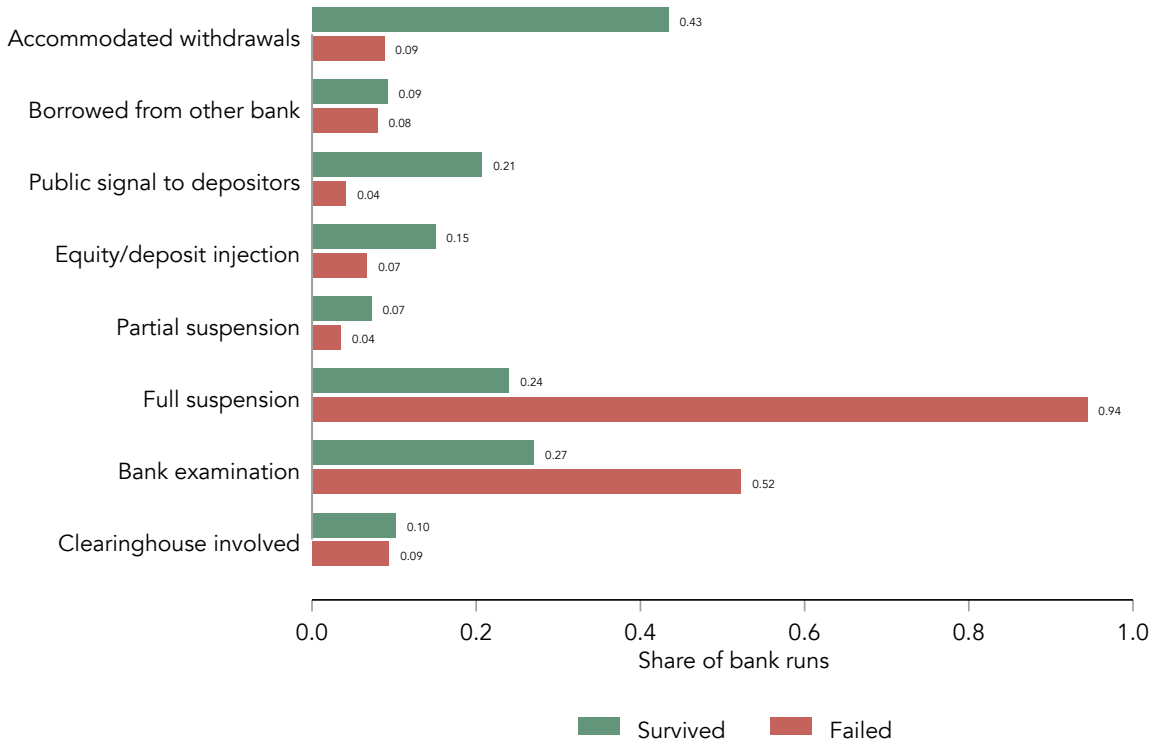
(vii) the bank underwent an examination by state supervisors, federal examiners, or by the local clearinghouse to ascertain its solvency.

Importantly, 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. Appendix B provides the exact prompts we use.

Figure 7 reports the share of run episodes mentioning each of these responses. We distinguish between runs that result in failure and runs 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 less common than full suspension of convertibility. Newspapers also mention that both surviving and failing banks borrow from other banks in about 9% of cases.[26]

[26]We note that this is likely to be underreported in newspapers, as banks may not want to make this public to avoid the stigma of needing assistance from other banks.

Figure 7: ***Bank Responses to Runs 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.

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 closed. Finally, in about 10% of runs, newspapers explicitly mention clearinghouse involvement, either through the provision of a loan, examination, or other measure.[27]

[27]Table A.8 examines whether the pass-through of runs to failure is lower for banks that are likely to be part of a local clearinghouse. We identify cities with clearinghouses using data from Jaremski (2018). National 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.

6.3 Non-Fundamental Runs and Bank Failures

Can non-fundamental runs trigger bank failures? To answer this question, we use additional information from the context provided in newspapers around bank runs 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 the information reported 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 44 runs on national banks that are classified as non-fundamental, indicating that such runs are uncommon. We further 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)	(2)	(3)
Run	0.37***		
	(0.056)		
Non-fundamental run		0.11**	0.13**
		(0.041)	(0.052)
Other run		0.38***	0.44***
		(0.058)	(0.057)
Strong fundamentals			-0.0100**
			(0.0040)
Strong fundamentals × Non-fundamental run			-0.13**
			(0.052)
Strong fundamentals × Other run			-0.34***
			(0.047)
Observations	268483	268483	268483
Mean dep. var.	0.0085	0.0085	0.0085

Notes: This table presents estimates of Equation (6). We define a bank to have "strong" fundamentals when $\text{Fundamentals}_{bt-1}$ is in the upper tercile of the historical distribution. Driscoll and Kraay (1998) standard errors in parentheses with a bandwidth of three years to allow for residual correlation within and across banks in proximate years. *,**, 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 in our sample is associated with a 37 percentage points higher probability of failure (column 1), this drops to 11% for non-fundamental runs. Thus, non-fundamental runs are much less likely to result in bank failure. Moreover, column 3 shows that strong banks (fundamentals in the upper tercile) subject to non-fundamental runs have a zero probability of failure (0%=13%-13%). 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.[28] Non-fundamentals runs, to the extent they take place at all, are unlikely to result in failure.

6.4 Adverse Public Signals, Runs, and Failures

In Section 5, we found that runs, especially those that do not result in failure, often happen in the context of news about the macro economy and the banking sector rather than in the context of bank-specific news. Motivated by this insight, we next study whether runs result in failure when they happen in the context of adverse public signals. Table 7 presents results from estimating variants of the following specification

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

where $\text{Adverse signal}_{rt}$ 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 3 showed that the occurrence of a run in the same city is 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 percentage points *less* likely to result in failure compared to the average run. The lower probability of failure for such runs is consistent with the notion that a run on another bank leads depositors to become "jittery." This finding is in line with depositors revising upward their belief that their own bank is insolvent. However, in some cases, this signal is not bank-specific and may lead depositors to mistakenly run on healthy banks. As a consequence, runs within the context of runs on other banks are less likely to lead to failure. However, the response

[28]The First National Bank of Sedalia was subject to a run in May 1894 following the 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 only 18%, and the OCC assessed 58% of its assets to be "worthless," both indicating deep insolvency. See description here: https://www.finhist.com/bank-runs/episodes/9353.html.

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

Dependent variable	Failure in t				
	(1)	(2)	(3)	(4)	(5)
Run	0.37***	0.39***	0.26***	0.18***	0.20***
	(0.056)	(0.052)	(0.053)	(0.058)	(0.053)
Run on other bank in same city		0.016***			0.021***
		(0.0047)			(0.0056)
Run on other bank in same city × Run		-0.11**			-0.12***
		(0.044)			(0.033)
Local business failure rate			0.76***		0.27**
			(0.18)		(0.12)
Local business failure rate × Run			6.65***		2.97**
			(1.23)		(1.31)
Business failure rate				1.31***	1.06**
				(0.36)	(0.43)
Business failure rate × Run				10.5***	7.89***
				(2.16)	(2.05)
Observations	278032	278032	238446	242910	238446
Mean dep. var.	0.0083	0.0083	0.0092	0.0091	0.0092

Notes: This table presents results from estimating variants of Equation (7). Driscoll and Kraay (1998) standard errors in parentheses with a bandwidth of three years to allow for residual correlation within and across banks in proximate years. *,**, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

is not necessarily irrational, as these runs still involve a probability of failure of 25%, suggesting many of these banks are indeed troubled.

In column 3 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 4 and 5 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 A.9 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. State-level non-financial business failures are from *Bradstreet's* and are available quarterly. Both bank runs and bank failures are preceded by and coincide with an elevated rate of business failures, which lead to asset losses for banks. The relation is especially strong

for bank failures. This evidence supports the key role of deteriorating fundamentals for understanding bank failures and runs. 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.

7 Consequences of Runs for Lending and Real Activity

In this final section, we study the consequences of runs and failures on financial intermediation and real economic activity. We first study the impact of bank runs on surviving banks at the bank level. We then turn to the impact of bank runs and failures on local aggregate lending, deposits, and manufacturing activity.

7.1 Bank-Level Consequences of Bank Runs Without Failure

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

$$\frac{Y_{bt+h} - Y_{bt-1}}{\text{Assets}_{bt-1}} = \alpha_b + \gamma_t + \beta^h \mathbf{1}[\text{Run}_{bt}^{Without\ failure}] + \epsilon_{bt+h}, \quad h = -5, \ldots, 5 \tag{8}$$

with the prediction horizon h running from five years before to five years after the distress episode. $\mathbf{1}[\text{Run}_{bt}^{Without\ failure}]$ 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; for failing banks, we cannot observe bank-level outcomes after the run. We measure the change in a given bank balance sheet item ($Y_{b,t+h} - Y_{b,t-1}$) relative to total assets in the year before the event, $\text{Assets}_{b,t-1}$, so magnitudes are relative to pre-event total assets. α_b is a bank fixed effect, and γ_t is a year fixed effect.

Panel (a) of Figure 8 shows the results from estimating Equation (8) 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% 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. Thus, runs have a lasting impact at the bank level even in the absence of bank failure.

Panel (b) of Figure 8 further explores heterogeneity across runs with and without

(temporary) suspension. Run episodes in which the bank is subject to a run but does not suspend at any point have relatively mild reductions in deposits of about 5%. 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.

Dynamics For Weak and Strong Banks As discussed in Section 2, if runs themselves are the primary cause of distress, then runs should typically be associated with severe outcomes, irrespective of initial bank fundamentals. In contrast, if runs themselves are mainly a trigger of distress for weak banks, then runs should be less costly for banks with sound fundamentals. Thus, we next ask: What are the implications of a run without failure across weak and strong banks? To answer this question, we estimate local projections of the form:

$$\begin{aligned}\frac{Y_{b,t+h} - Y_{b,t-1}}{\text{Assets}_{b,t-1}} = \alpha_b + \gamma_t &+ \beta_S^h \mathbf{1}[\text{Run}_{b,t}^{\textit{Without failure}}] \times \text{Strong Fundamentals}_{b,t-1} \\ &+ \beta_W^h \mathbf{1}[\text{Run}_{b,t}^{\textit{Without failure}}] \times \text{Weak Fundamentals}_{b,t-1} \\ &+ \epsilon_{b,t+h}, \qquad h = -5, \ldots, 5\end{aligned} \tag{9}$$

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

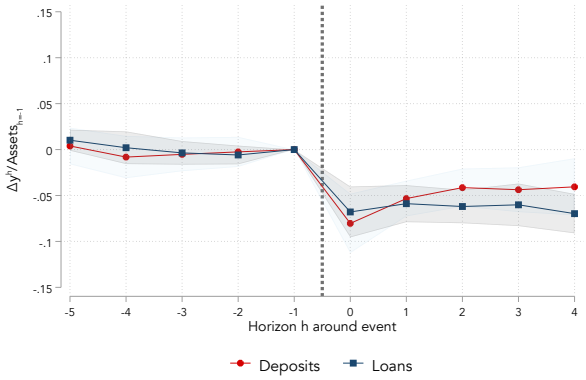
Panels (c) and (d) of Figure 8 present the results. Runs without failure lead to larger deposit declines for banks with weak fundamentals. Banks with strong fundamentals see essentially no decline in loans and deposits, whereas banks with weak fundamentals see a persistent decline in deposits and lending of about 8%. Thus, bank fundamentals not only determine whether runs trigger bank failure; they also shape the consequences of bank runs when banks survive runs.

Taken together, the dynamics of deposits and loans around bank runs reinforce the notion that runs tend to be associated with severe distress, especially when they happen in banks with weak fundamentals. Runs on banks with sound fundamentals have little impact on the bank's long-term viability.

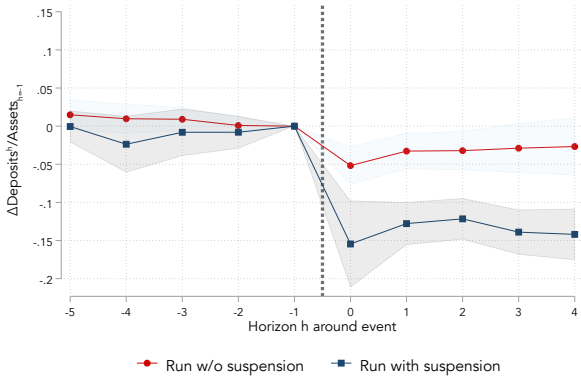
Dynamics Around Non-Fundamental Runs A concern with studying the dynamics of deposits and loans around without failure is that such runs do not happen randomly but occur in response to bad news about the economy that leads depositors to run as a precautionary measure. These shocks can simultaneously reduce the demand for loans

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

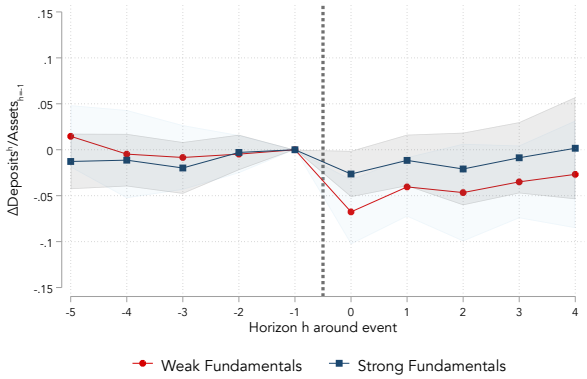
(a) *Deposits and loans: bank runs without failure*



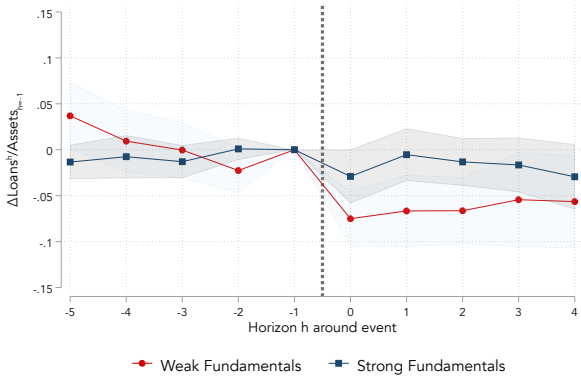
(b) *Deposits: runs with and without temporary suspension*



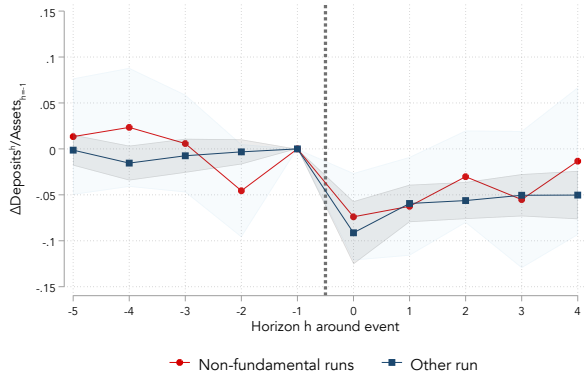
(c) *Deposits: weak vs strong banks*



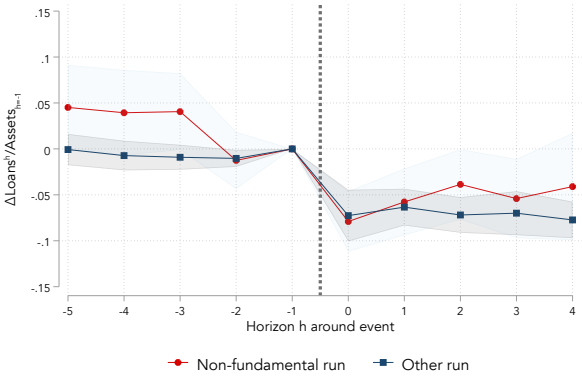
(d) *Loans: weak vs strong banks*



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



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



Notes: This figure reports coefficients from estimating Equations (8) (panels a and b), (9) (panels c and d), and (10) (panels e and f). All episodes are runs without bank failure. Shaded areas represent 95% confidence intervals based on Driscoll and Kraay (1998) standard errors with a bandwidth of three years to allow for residual correlation within and across banks in proximate years. Strong and weak fundamentals indicates when $\text{Fundamental}_{b,t-1}$ is in either the upper or lower tercile.

and deposits. To make some progress on the causal effect of runs, we replace the shock with our measure of non-fundamental runs discussed in Section 6.3. 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:

$$\frac{Y_{bt+h} - Y_{bt-1}}{\text{Assets}_{bt-1}} = \alpha_b + \gamma_t + \beta^h_{NF}\mathbf{1}[\text{Runs}^{Without\ failure,\ non-fund}_{bt}] + \beta^h_{Other}\mathbf{1}[\text{Run}^{Without\ failure,\ other}_{bt}] + \epsilon_{bt+h}, \quad h = -5, \ldots, 5. \tag{10}$$

Figure 8 panels (e) and (f) 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, which is 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 w/o suspension" 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.

7.2 Local Consequences of Runs and Failures

We next examine the consequences of bank runs at the local aggregate level. As we have seen, most banking crises from 1863 to 1934 had a strong regional component. We can use our detailed data to exploit cross-regional variation to understand the local consequences of banking sector distress. We first examine the impact on city-level aggregate bank deposits and lending. We then provide evidence for the effect of runs on city-level manufacturing activity.

7.2.1 Deposits and Lending

Runs on weak vs strong banks We study the local economic consequences of bank runs on local deposits and lending, distinguishing between whether runs affect weak or strong banks. We estimate impulse responses from local projections of the following form:

$$g^y_{c,t-1,t+h} = \alpha_c + \beta^h_S\mathbf{1}[\text{Run}^{Strong}_{c,t}] + \beta^h_I\mathbf{1}[\text{Run}^{Interm}_{c,t}] + \beta^h_W\mathbf{1}[\text{Run}^{Weak}_{c,t}] + X_{c,t-1}\Gamma^h + \epsilon_{c,t+h}, \quad h = 0, ..., H. \tag{11}$$

The outcome variable, $g^{y}_{c,t-1,t+h}$, is the symmetric growth rate of a variable such as total lending in city c from year $t-1$ to $t+h$, defined as $g^{y}_{c,t-1,t+h} = \frac{y_{c,t+h} - y_{c,t-1}}{0.5(y_{c,t+h} + y_{c,t-1})}$. The symmetric growth rate is bounded between -2 and 2. We employ this definition of growth to accommodate the possibility that an outcomes in a local area goes to zero.[29] Outcome variables are constructed based on aggregating national bank balance sheets to the city and year level.

The shocks, $\mathbf{1}[\text{Run}^{Strong}_{c,t}]$, $\mathbf{1}[\text{Run}^{Interm}_{c,t}]$, and $\mathbf{1}[\text{Run}^{Weak}_{c,t}]$, capture local exposure to runs on banks with strong, intermediate, and weak fundamentals. These measures are defined as indicator variables that equal one if a bank with fundamentals in category j is subject to a run in city c and year t, and zero otherwise. Fundamentals are defined as the top (strong), middle (intermediate), and bottom (weak) terciles of the fundamentals measure, $Fundamentals_{b,t-1}$. By using indicator variables, we effectively exploit the extensive margin of the variation in whether a city is exposed to a run; results are similar when using asset-weighted exposure to capture the share of banks subject to runs. In $X_{c,t-1}$, we include $L = 3$ yearly lags of both the run shocks and the dependent variable, as is standard in the local projections framework (Jordà, 2005). The local projection impulse responses are thus the sequence of estimated coefficients $\{\hat{\beta}^h_S, \hat{\beta}^h_I, \hat{\beta}^h_W\}$.

Figure 9 presents the impulse responses of city-level deposits (panel a) and loans (panel b) to innovations in the city-level runs on weak and strong banks. Runs predict a reduction in city-level deposits and loans. However, it matters whether it is weak or strong banks that are run. Runs are associated with significantly larger reductions in deposits and lending when they affect weak banks. Runs on weak banks lead to a reduction in city-level deposits and lending of over 40% in the years immediately after the shock. In contrast, runs on strong banks are associated with declines in deposits and lending of around 10%. This is in line with the view that runs themselves are not universally associated with severe crises but rather result in severe economic consequences when bank fundamentals are weak.

Non-fundamental and other runs In Figure 8, we saw that non-fundamental runs led to modest but non-trivial reductions in bank-level deposits and lending. Figure 9 panels (c) and (d) report the implications of such runs for city-level deposits and lending based

[29] Results are similar if we use the log of $y_{c,t}$ as the outcome, but we prefer the symmetric growth rate to avoid exit and reentry of mostly smaller cities into the estimation panel.

on estimating:

$$g^{y}_{c,t-1,t+h} = \alpha_c + \beta^h_{NF}\mathbf{1}[\text{Run}^{Non-fund}_{c,t}] + \beta^h_{Other}\mathbf{1}[\text{Run}^{Other}_{c,t}] \tag{12}$$

$$+ X_{c,t-1}\Gamma^h + \epsilon_{c,t+h}. \quad h = 0, ..., H, \tag{13}$$

$\mathbf{1}[\text{Run}^{Non-fund}_{c,t}]$ is an indicator for whether there is a non-fundamental run in city c and year t as defined in Section 6.3 and $\mathbf{1}[\text{Run}^{Other}_{c,t}]$ is an indicator for other runs. While non-fundamental runs reduce deposits and lending at affected banks, Figure 9 shows they have essentially no effect on local deposits and lending. This is presumably because deposits are reallocated relatively seamlessly to other local banks during such runs.

Runs with and without failure Next, we study the consequences of runs with and without failure. This provides another test to address whether runs alone can be associated with severe economic consequences, or whether bank failures, indicative of bank insolvency, are necessary for runs to be associated with severe crises.

To do this, we estimate impulse responses from the following local projections specification:

$$g^{y}_{c,t-1,t+h} = \alpha_c + \beta^h_{RNF}\mathbf{1}[\text{Run}^{Without\ failure}_{c,t}] + \beta^h_{RWF}\mathbf{1}[\text{Run}^{With\ failure}_{c,t}] \tag{14}$$

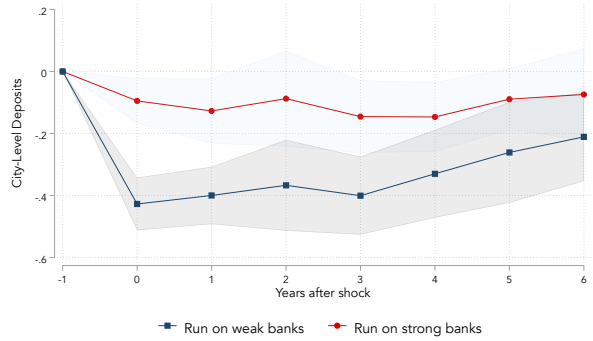
$$+ X_{c,t-1}\Gamma^h + \epsilon_{c,t+h}, \quad h = 0, ..., H.$$

$g^{y}_{c,t-1,t+h}$ is again the symmetric growth rate of aggregate city-level loans or deposits from $t-1$ to $t+h$. We consider two mutually exclusive bank distress episodes: (i) run without failure, and (ii) run with failure. Each measure is defined as an indicator variable for whether a city is subject to a given distress episode in year t. This exercise allows us to separately study the consequences of episodes that are closer to pure liquidity events from episodes involving bank insolvency. Given that the likelihood of failure conditional on a run is strongly predictable based on bank fundamentals, this exercise complements the previous analysis on runs across banks with strong and weak fundamentals. However, instead of using an *ex ante* measure of bank health, here we use an *ex post* measure of bank distress.

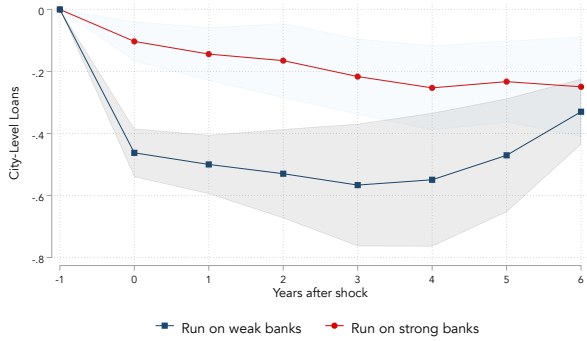
Panels (e) and (f) in Figure 9 present the results from estimating Equation (14). Not all bank distress episodes are alike. Runs with failure translate into substantially larger contractions in city-level deposits and lending than runs without failure. Runs without failure lead to a small and temporary decline in deposits that recovers after a few years. The effect on loans is more persistent but modest in size. Thus, bank distress involving

Figure 9: ***Consequences of Runs for City-Level Deposits and Lending***

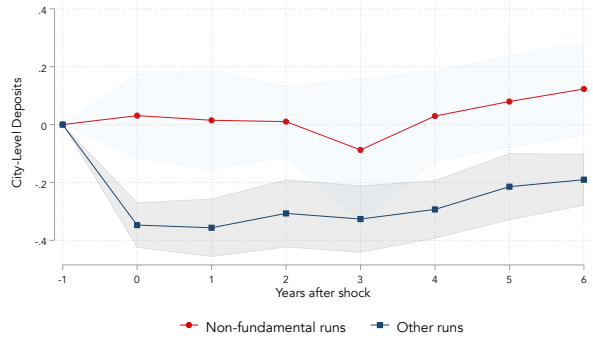
(a) *Impact of runs on deposits, weak vs strong banks*



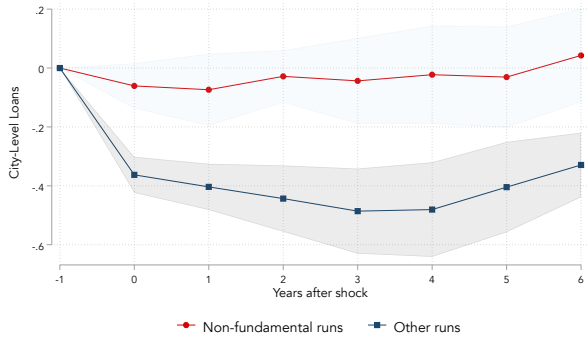
(b) *Impact of runs on loans, weak vs strong banks*



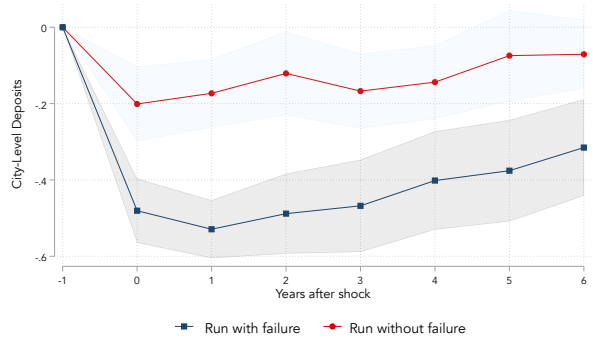
(c) *Impact of runs on deposits, non-fundamental runs*



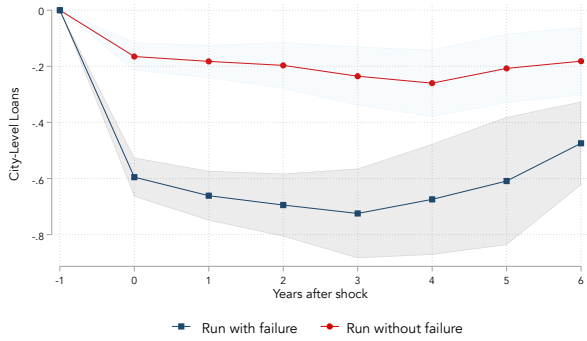
(d) *Impact of runs on loans, non-fundamental runs*



(e) *Impact of run with and without failure on deposits*



(f) *Impact of run with and without failure on loans*



Notes: This figure presents impulse responses based on estimation of Equation (11) (panels a and b), Equation (12) (panels c and d), and Equation (14) (panels e and f). The analysis is based on a city-level annual panel. Loans, deposits, and bank distress are based on aggregating the sample of national banks from 1863-1934 to the city level at an annual frequency. The units are in percent divided by 100. Error bands represent 95% confidence intervals based on standard errors dually clustered on city and year.

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 runs to involve severe local deposit and lending contractions.

In terms of magnitudes, Figure 9 shows that if a city experiences a run that results in

bank failure, deposits decline by around 50% and loans by 60%. The effect is persistent, although there is a slight recovery. These effects are large in part because of restrictions on branching and acquisitions, which meant that bank failure would lead to persistent reductions in banking services in a city (Quincy and Xu, 2025). This is especially true in smaller cities with fewer banks. In contrast, if a city is exposed to a run that does not result in bank failure, both deposits and loans decline by less than 10%. While deposits fully recover after four years, loans remain slightly below trend.

7.2.2 Manufacturing Activity

As a final exercise, we study the real economic effects of runs at the local city level. We use a newly collected dataset on local economic activity constructed from *Bradstreet's*, a business journal that provides city-level summaries of economic conditions at a weekly frequency in major cities for various sectors, including manufacturing, retail trade, and wholesale trade.[30] We focus on *Bradstreet's* description of activity in the manufacturing sector. Using the short textual descriptions, we classify economic conditions into poor (1), fair (2), or good (3). We normalize our index of manufacturing activity to have the same variance as the cyclical component of industrial production (IP), defined as the deviation of log IP from its one-sided three-year moving average. This analysis is covers 30 major cities from 1917 through 1935, providing high-frequency evidence on the consequences of runs for the real economy.

Before proceeding, we note that the results based on our index of manufacturing activity from *Bradstreet's* are mainly driven by larger cities during the Great Depression. Moreover, the index is based on qualitative information, so the transformation to a numeric index may contain measurement error. Nevertheless, in the appendix, we show that the aggregated city-level manufacturing index constructed from *Bradstreet's* is highly correlated with the cyclical component of industrial production. It captures the major 1920-21 recession and the Great Depression, indicating that it contains valuable information at the business cycle frequency.

Runs on weak vs strong banks We first study the city-level consequences of runs on weak versus strong banks. We estimate impulse responses to run events using the

[30]The underlying data are weekly for 1917 through March 11, 1933, and monthly for the remainder of 1933 through 1933. For the latter period, we fill values forward to retain a weekly panel structure. See Appendix C.1 for details on the *Bradstreet's* data and the construction of the manufacturing activity index.

following local projections specification:

$$Y^{Manuf}_{c,t+h} = \alpha_c + \beta^h_S \mathbf{1}[\text{Run}^{Strong}_{c,t}] + \beta^h_I \mathbf{1}[\text{Run}^{Interm}_{c,t}] + \beta^h_W \mathbf{1}[\text{Run}^{Weak}_{c,t}] + X_{c,t-1}\Gamma^h + \epsilon_{c,t+h}, \quad h = 0, ..., H. \tag{15}$$

$Y^{Manuf}_{c,t}$ is the city-level manufacturing index is city c and week t. α_c is a city fixed effect. The shocks $\mathbf{1}[\text{Run}^{Strong}_{c,t}]$, $\mathbf{1}[\text{Run}^{Interm}_{c,t}]$, and $\mathbf{1}[\text{Run}^{Weak}_{c,t}]$ are indicator variables for whether a strong, intermediate, or weak bank was subject to a run in city c and week t based on the tercile of $Fundamentals_{b,t-1}$. We include 24 weekly lags of both the dependent and the innovation variables in $X_{c,t-1}$ and study responses out to 80 weeks (1.5 years).

Figure 10a shows that runs lead to substantially worse declines in city-level manufacturing when they occur in weak banks. Runs on strong banks do not predict a deterioration in city-level manufacturing; the estimates are slightly positive, close to zero, and not statistically significant. In contrast, runs on weak banks lead to a gradual decline in manufacturing activity over the subsequent year. Recall that the manufacturing index is normalized to have the same mean and variance as the cyclical component of aggregate industrial production. Thus, in terms of magnitudes, runs on weak banks in a city are associated with a roughly 5% decline in city industrial production after one year.

Runs with and without failure Finally, we study the city-level consequences of runs with and without failure for manufacturing activity. We estimate impulse responses from the following local projection at the weekly level.

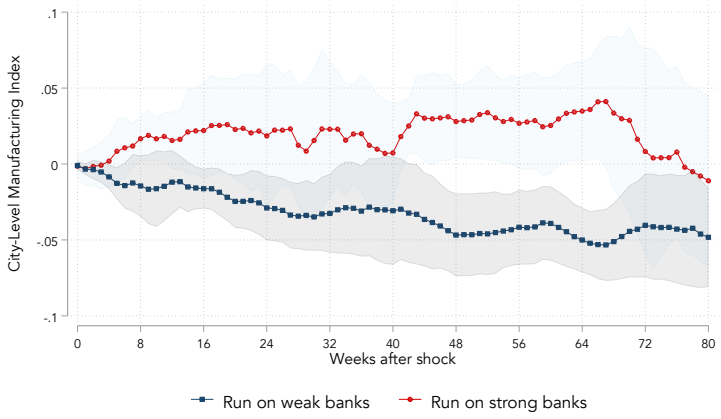
$$Y^{Manuf}_{c,t+h} = \alpha_c + \beta^h_{RNF} \mathbf{1}[\text{Run}^{Without\ failure}_{c,t}] + \beta^h_{RWF} \mathbf{1}[\text{Run}^{With\ failure}_{c,t}] + X_{c,t-1}\Gamma^h + \epsilon_{c,t+h}, \quad h = 0, ..., H. \tag{16}$$

In this specification, $\mathbf{1}[\text{Run}^{Without\ failure}_{c,t}]$ is an indicator for whether a city c is subject to a run without failure in week t, and $\mathbf{1}[\text{Run}^{With\ failure}_{c,t}]$ is an indicator for whether there is a run with a bank failure. We define run as involving failure if the bank fails within 30 days of the date of the run, based on the evidence that most failures occur within 30 days of the run (see Figure 6).

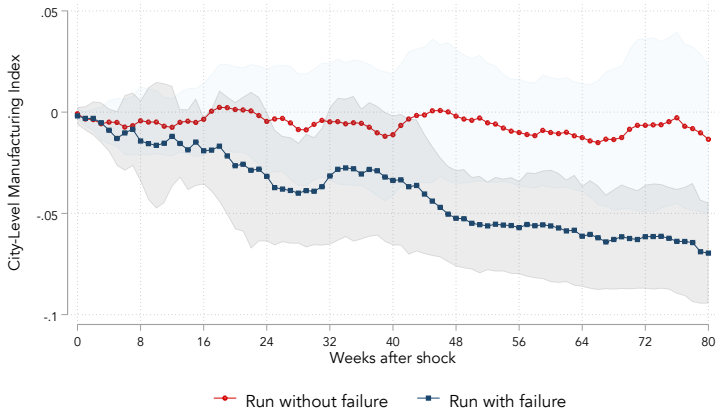
Figure 10b reveals that runs with bank failures lead to substantially worse declines in local economic activity than runs without failure. The response of manufacturing activity to runs without failure (run with failure) is quantitatively similar to the response to runs on strong (weak) banks in panel (a). Runs without failure do not result in significantly lower manufacturing activity within the next 18 months. Runs with failure predict a

Figure 10: ***Consequences of Runs for City-Level Manufacturing Activity***

(a) *Impact of runs on manufacturing index, weak vs strong banks*



(b) *Impact of runs with and without failure on manufacturing index*



Notes: This figure presents impulse responses based on estimation of Equation (15) (panel a) and Equation (16) (panel b). The analysis is based on a city-level weekly panel from 1917 to 1935. The outcome variable is a city-level weekly index of manufacturing activity, which we normalize to have the same mean and variance as industrial production; see Appendix C.1 for details. The units are in percent divided by 100. Error bands represent 95% confidence intervals based on standard errors dually clustered on city and time (week).

decline in manufacturing activity of over 5%.

Overall, the evidence on local consequences of runs for credit markets and real activity tempers the view that runs that originate as pure liquidity events can generate severe disruptions in local credit markets and real activity. Runs on strong banks and non-fundamental runs carry limited adverse effects beyond the affected banks. Instead, the evidence indicates that poor fundamentals are necessary for runs to generate severe local financial disruptions. A key channel through which runs disrupt real activity is through bank failure, which, in turn, usually requires that a bank is fundamentally insolvent, or at least very weak in terms of fundamentals (Correia, Luck and Verner, 2025). Thus, runs

should not be seen as universally carrying high economic costs; rather, runs involve large economic contractions when bank fundamentals are particularly weak.

8 Conclusion

In this paper, we apply large language models to historical newspapers to study bank runs recorded in digitally available newspapers in the United States from 1863 to 1934. Our novel database uncovers over three thousand bank runs, allowing for the first comprehensive micro-level evidence on the causes and consequences of bank runs. We combine these data with balance sheet information on banks. Our data allow us to derive several key insights about the nature of banking crises.

We provide six main findings. First, runs are more likely in banks with observably weaker fundamentals, broadly consistent with fundamental-based panic runs. Second, strong banks can also be run, especially in response to adverse news about the economy or the banking system, in line with information-based theories of runs. Third, most runs do not result in bank failure, and runs typically only trigger the failure of weak banks. Fourth, we establish that banks with strong fundamentals manage to survive runs through various mechanisms, including interbank cooperation, equity injections or loans, examination, and suspension, consistent with information-based theories of runs. Fifth, healthy banks can survive bank runs without any other major consequences, while weak banks that survive runs remain scarred by the run in the medium term. Finally, at the local level, weak fundamentals are necessary for bank runs to result in substantial contractions in financial intermediation and real manufacturing activity. Moreover, bank failure is an important mechanism for capturing the local economic costs of runs.

Taken together, our findings lend little support to the view that small shocks can result in large jumps to bad equilibria via runs on demandable debt. In contrast, our findings suggest that poor bank fundamentals are necessary for bank runs to translate into failure and, more broadly, for bank distress to generate severe economic consequences. While runs can occur in both weak and strong banks, poor fundamentals are necessary for runs to result in bank failures. Failures, in turn, are a key proxy for economic distress resulting from turmoil in the banking sector (Bernanke, 1983). Events that are primarily liquidity driven are less commonly associated with severe economic outcomes and should be less of a concern than solvency-driven crises.

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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.5c). 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.

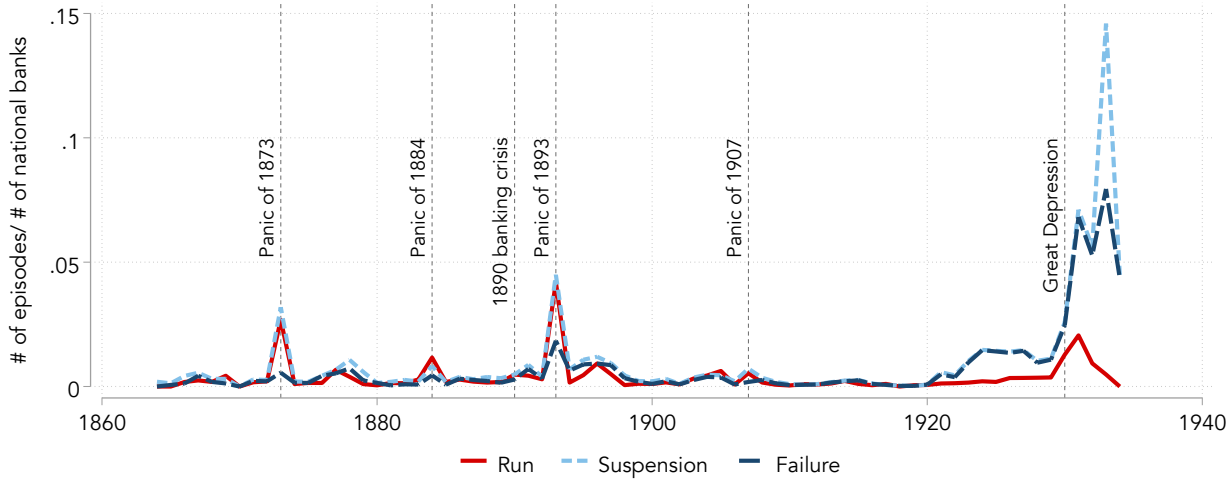
subject to runs that do not fail. Banks subject to runs that do not fail look similar to ordinary banks not subject to any form of distress. Moreover, failing banks have weak bank observables, irrespective of whether they are subject to a run before failure.

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, Luck and Verner, 2026).

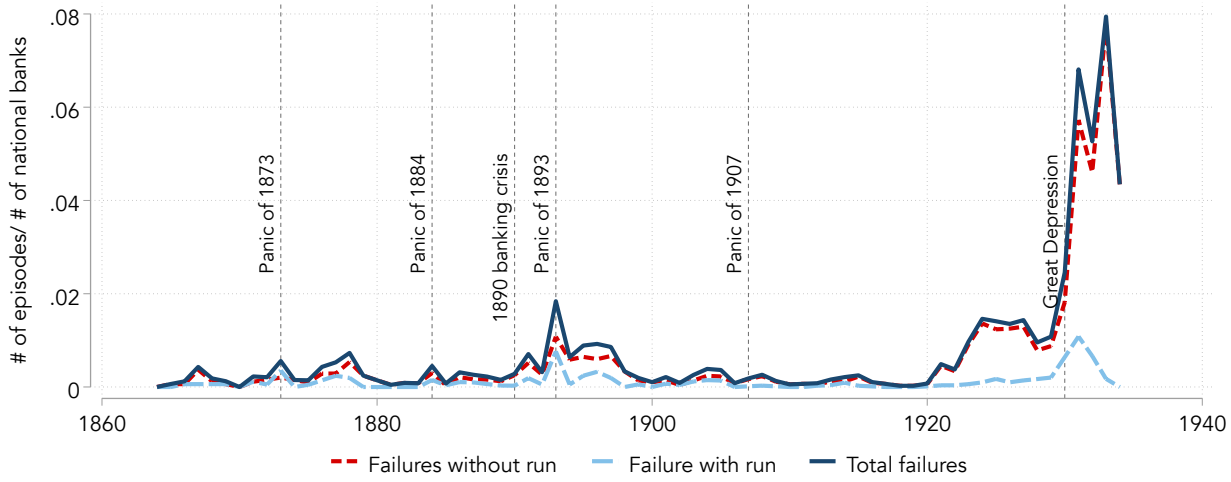
A.2 Additional Figures

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

(a) *Runs, suspensions, and failures*



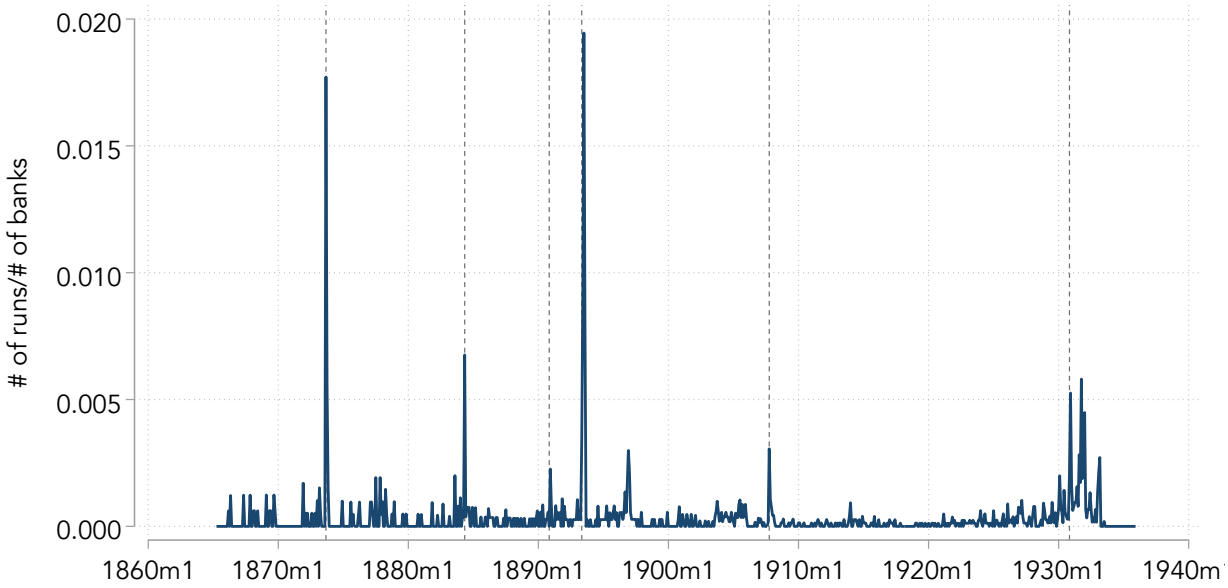
(b) *Failures with and without runs*



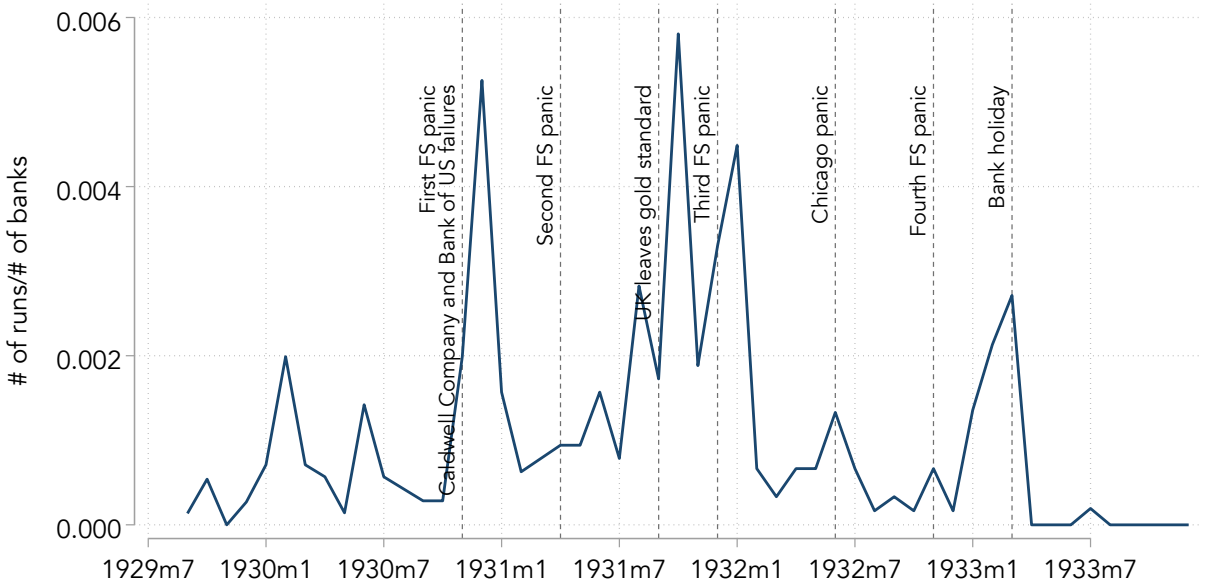
Notes: This figure plots the ratio of the number of national banks subject to a distress episode over the total number of national banks in each year. In panel (a), we report the rate of bank runs, suspensions, and failures. In panel (b), we show the number of bank failures (OCC receiverships) that are 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***

(a) *Full sample:1863-1934*

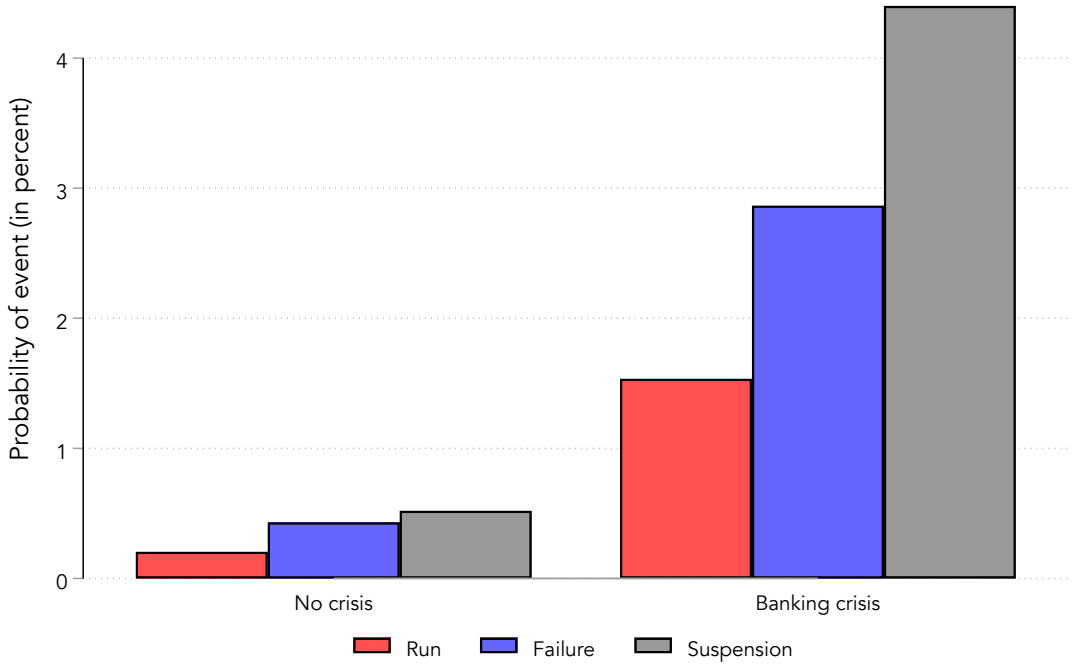


(b) *Great Depression*



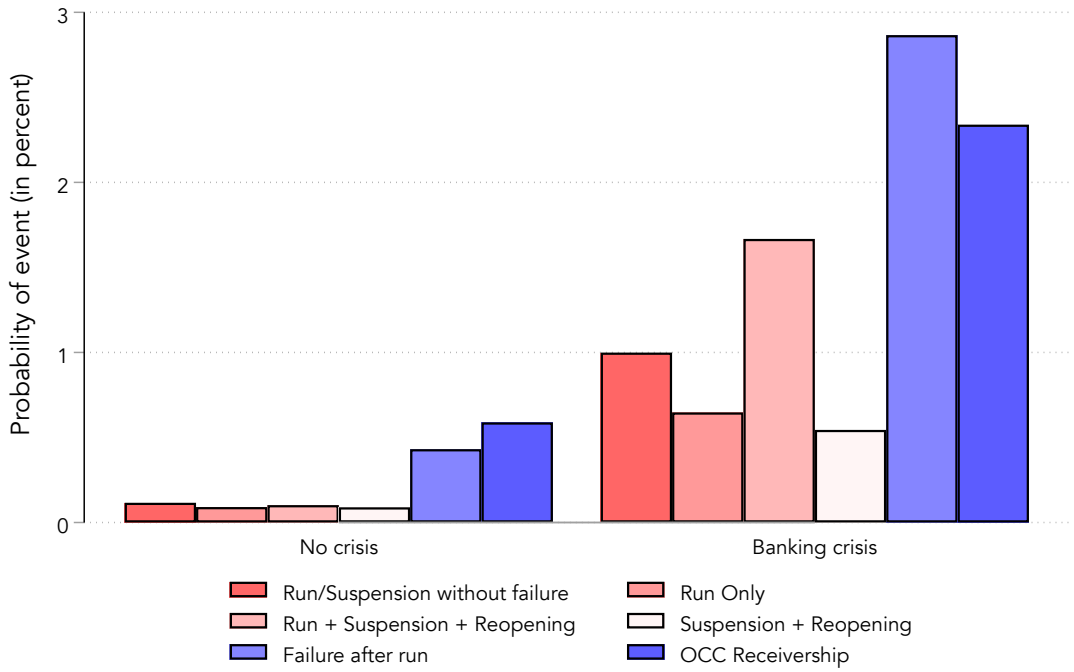
Notes: Vertical lines in panel (a) represent the month of a banking panic from Baron, Verner and Xiong (2021). Vertical lines in panel (b) represent key events during the Great Depression. "FS panic" refers to the banking panics as classified in Friedman and Schwartz (1963).

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, Verner and Xiong (2021). The sample is all national banks during 1863-1934.

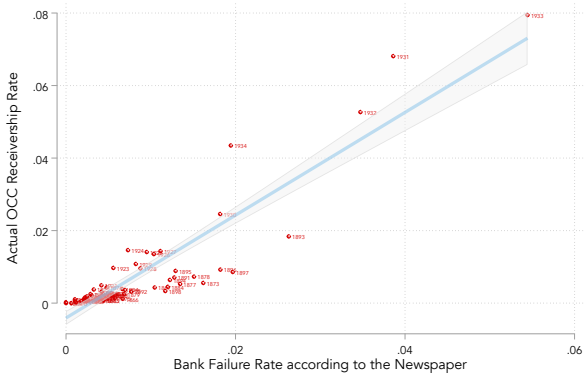
Figure A.4: ***Probability of Bank Distress Episodes for National Banks During and Outside of Banking Crises***



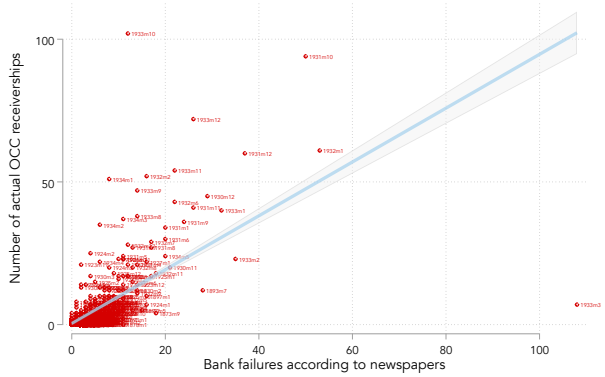
Notes: The figure plots the probability of various bank distress episodes during and outside of years identified as banking crises in Baron, Verner and Xiong (2021). The sample is based on all national banks from 1863-1934.

Figure A.5: *Data Quality Validation*

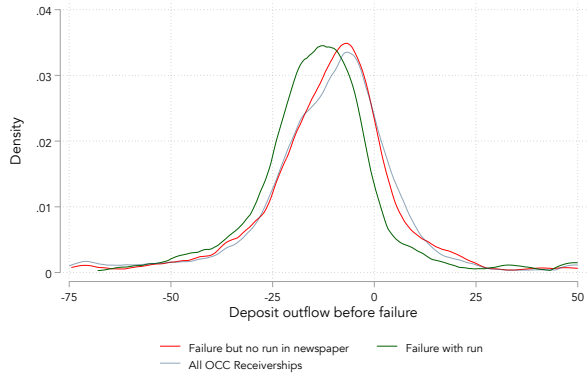
(a) *National Bank Failure Rates: Annual*



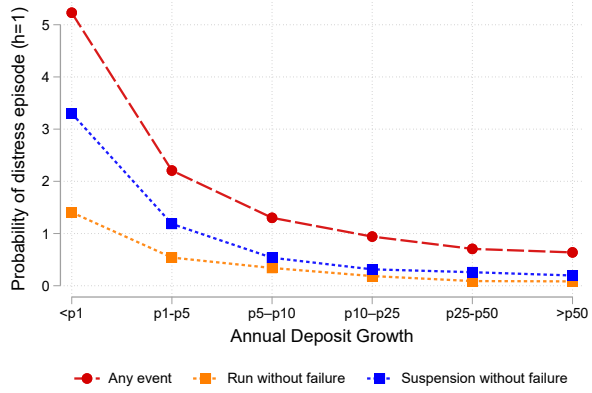
(b) *Number of National Bank Failures: Monthly*



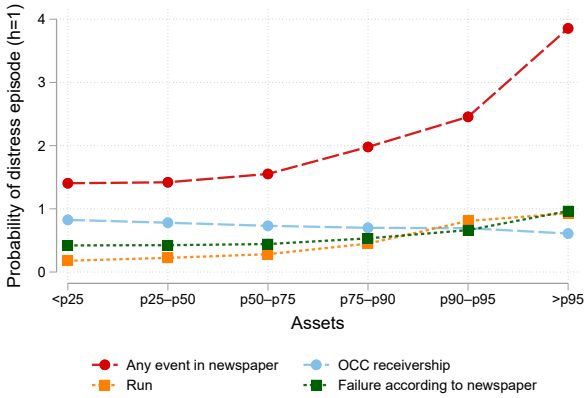
(c) *Deposit Outflows*



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

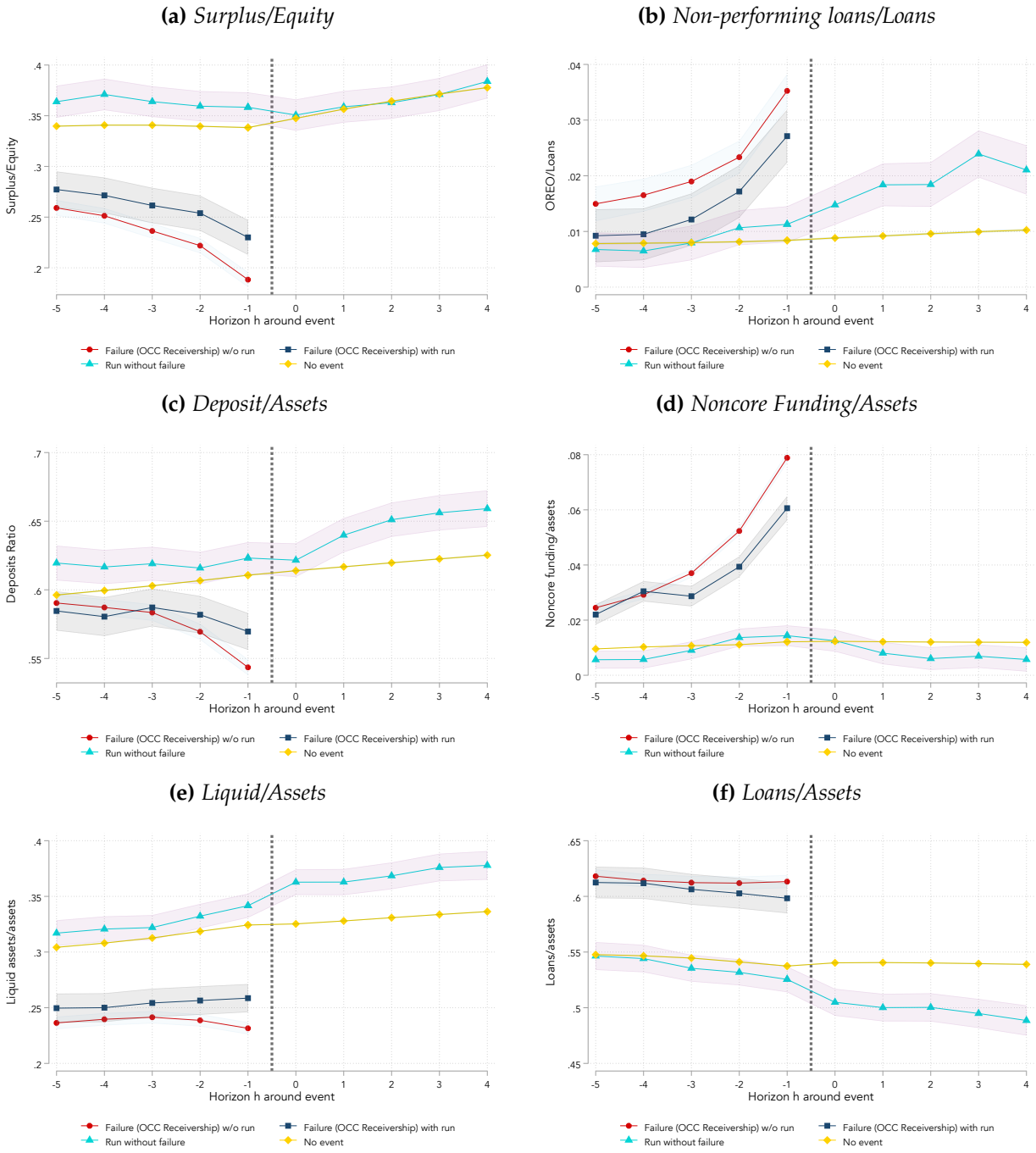


(e) *Events by bank size*



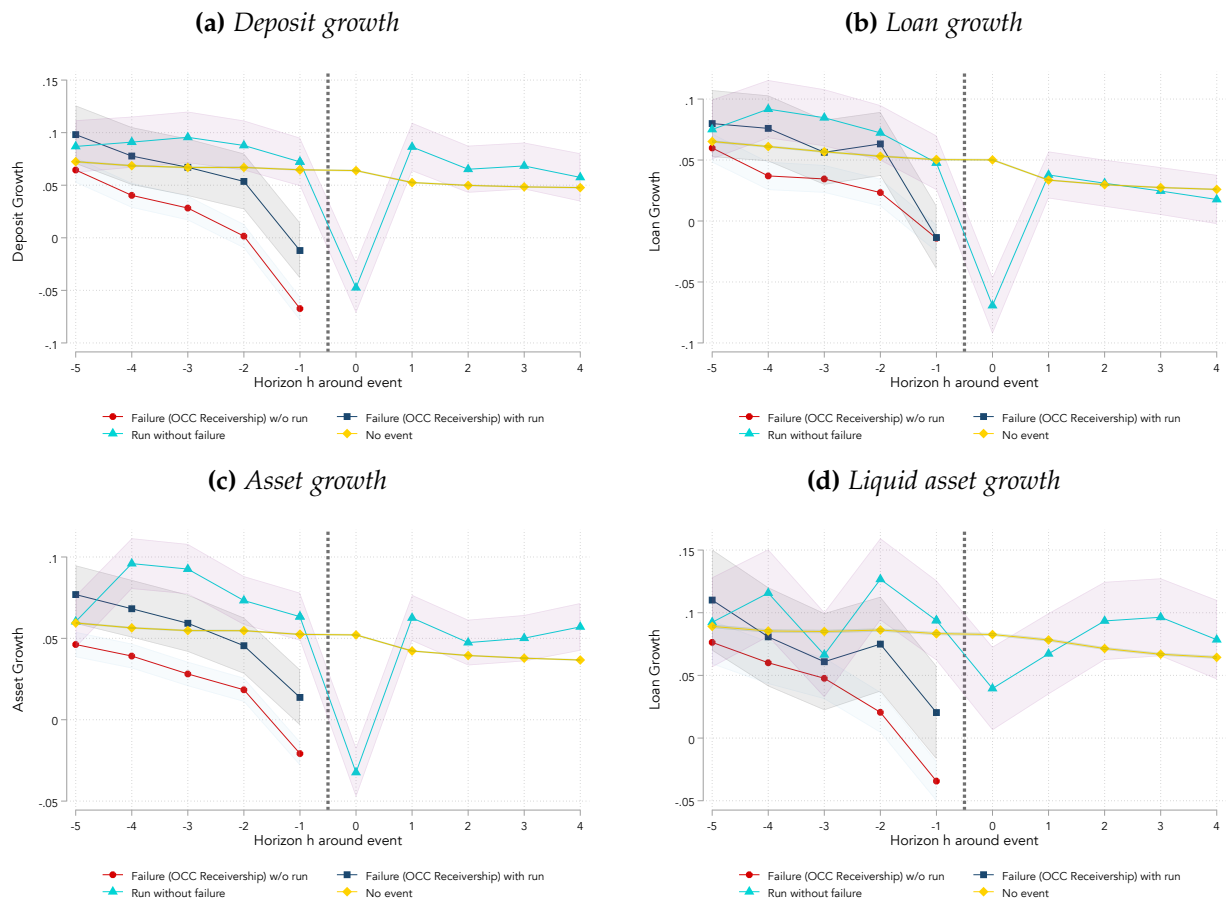
Notes: The sample in all panel is based on national banks during 1863-1934. In panel (d), the sample is all OCC national bank receiverships during 1864-1934. Deposit outflows before failure are calculated using the total deposits reported in the last call report before failure and deposits at failure.

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



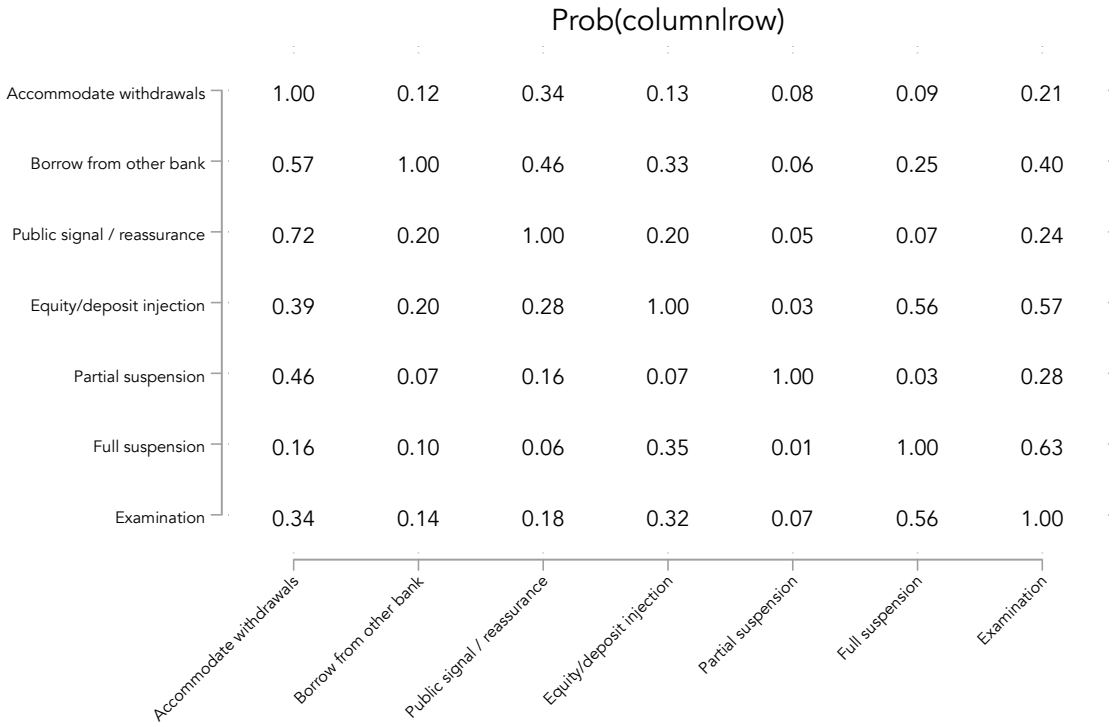
Notes: This figure plots the coefficients from estimating Equation (A.1). Non-performing loans are proxied by the line item "other real estate owned" (OREO). Shaded areas represent 95% confidence bands based on Driscoll and Kraay (1998) standard errors with a bandwidth of three years to allow for residual correlation within and across banks in proximate years. 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 based on Driscoll and Kraay (1998) standard errors with a bandwidth of three years to allow for residual correlation within and across banks in proximate years.

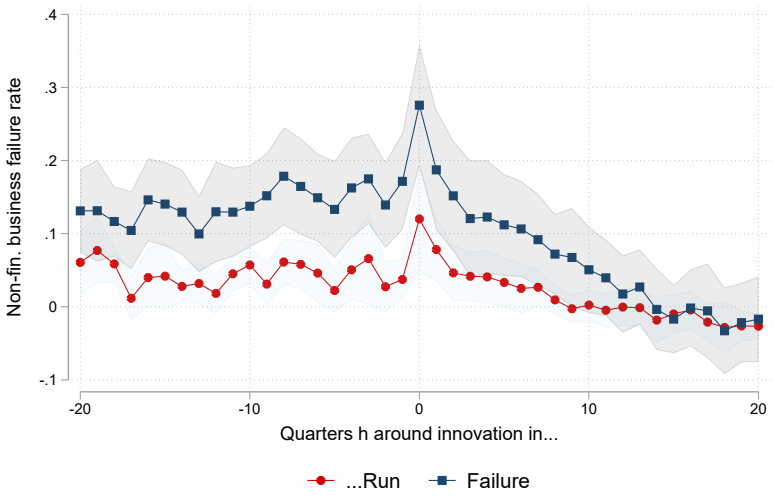
Figure A.8: ***Responses to Bank Runs: Conditional Probabilities***



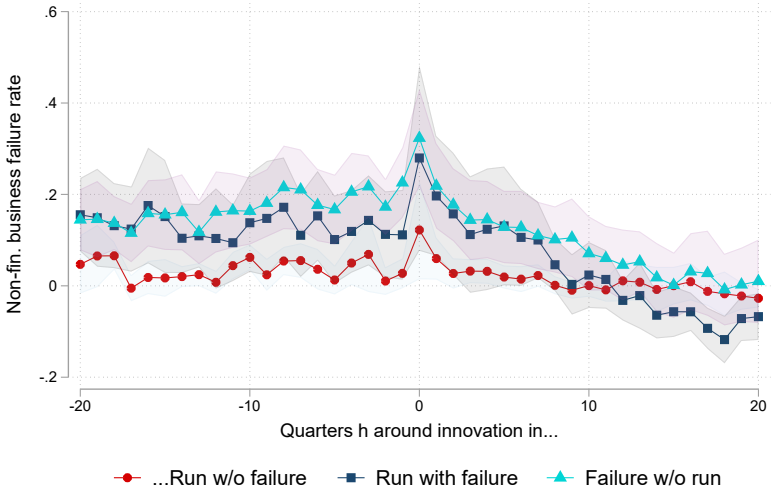
Notes: This figure reports the probability of a response listed in each column, conditional on the bank taking the response in a given row. See Figure 7 for further details on the classification of responses.

Figure A.9: ***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

$$\text{Business failure rate}_{st+h} = \alpha_s + \text{Bank distress}_{st} + u_{t+h}, \quad h = -20, ..., 0, ..., 20. \tag{A.2}$$

Business failure rate$_{st+h}$ is the state-level non-financial business failures rate in state s for quarter $t+h$, and Bank Distress$_{st}$ is the share of banks exposed to a run or failure in state s and quarter t. 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 on Driscoll and Kraay (1998) standard errors with a bandwidth of three years. The specification also controls for quarter fixed effects to capture seasonality in the failure rate.

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	0.46***	0.73***	1.35***
	(0.058)	(0.16)	(0.19)
Major banking panic month	1.42**	-0.70***	1.29**
	(0.58)	(0.18)	(0.62)
May 1884 (NYC, PA, NJ)	11.9	2.32***	4.00
	(7.40)	(0.79)	(3.84)
Nov. 1890 (New York City, NY)	1.10***	-0.028	-1.19***
	(0.33)	(0.12)	(0.33)
Dec. 1896 (IL, MN, WI)	6.11**	1.35	4.98***
	(2.40)	(1.26)	(1.67)
Dec. 1899 (Boston, MA; NYC, NY)	2.77*	2.35***	3.81***
	(1.44)	(0.73)	(0.36)
June through July 1901 (NY: Buffalo; NYC)	0.77***	3.35***	6.31***
	(0.020)	(0.041)	(0.035)
Oct. 1903 (PA, MD)	1.77***	-0.65***	-0.69***
	(0.020)	(0.041)	(0.035)
Dec. 1905 (Chicago, IL)	1.27***	-0.15***	1.81***
	(0.020)	(0.041)	(0.035)
Jan. 1908 (NYC)	1.77***	4.35***	7.31***
	(0.020)	(0.041)	(0.035)
Aug. through Sept. 1920 (Boston)	2.77***	0.35***	1.31***
	(0.020)	(0.041)	(0.035)
Nov. 1920 - Feb. 1921 (ND)	-0.23***	2.35***	13.3***
	(0.020)	(0.041)	(0.035)
July 1926 (FL, GA)	1.77***	-0.65***	2.31***
	(0.020)	(0.041)	(0.035)
March 1927 (FL)	6.77***	1.35***	12.3***
	(0.020)	(0.041)	(0.035)
July through Aug. 1929 (FL)	17.8***	7.35***	23.3***
	(0.020)	(0.041)	(0.035)
N	10790	10790	10790
Mean dep. var.	0.36	0.80	1.01

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, Verner and Xiong (2021) and regional banking crises are from Jalil (2015). Sample of events 1863 through 1934. Driscoll and Kraay (1998) standard errors in parentheses with a bandwidth of three years. *,**, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table A.2: *Predictability of Bank Runs Based on Fundamentals, Runs on Other Banks, and Macroeconomic Variables*

Dependent variable	Run in $t+1$					
	(1)	(2)	(3)	(4)	(5)	(6)
Bank fundamentals:						
Surplus/Equity	-0.21	-0.25	-0.32*	-0.36**	-0.43**	-0.39**
	(0.13)	(0.16)	(0.17)	(0.14)	(0.19)	(0.19)
Noncore funding	7.83***	7.83***	6.77**	7.06**	6.81**	7.82***
	(2.57)	(2.39)	(2.58)	(2.81)	(2.62)	(2.69)
Surplus/Equity × Noncore funding	-5.31**	-7.37***	-5.98**	-4.79*	-5.47**	-6.95**
	(2.57)	(2.46)	(2.60)	(2.69)	(2.64)	(2.71)
Liquid Assets/Assets	-0.54**	-0.16	-0.69*	-0.63**	-0.64*	-0.19
	(0.25)	(0.16)	(0.36)	(0.29)	(0.36)	(0.17)
Deposits/Assets	0.72*	0.39*	0.21	0.54	0.42	0.49*
	(0.39)	(0.22)	(0.33)	(0.45)	(0.33)	(0.28)
Asset Growth (3 years)	-0.13	0.03	0.02	-0.10	-0.00	-0.02
	(0.13)	(0.07)	(0.09)	(0.11)	(0.09)	(0.09)
Macro conditions:						
NB failure rate			-0.92		-1.97	
			(4.70)		(4.58)	
NB run rate			1.37		9.20	
			(18.39)		(18.49)	
Stock market return			-0.63**			
			(0.28)			
Real GDP growth			0.25		0.00	
			(0.78)		(0.71)	
Local conditions:						
Run on other bank in same city				2.86***	2.84***	2.49***
				(0.93)	(0.92)	(0.78)
Local business failure rate				8.34***	0.30	0.34
				(2.51)	(5.37)	(6.31)
N	286382	286382	242910	239863	239863	239863
Mean dep. var	.33	.33	.36	.35	.35	.35
Year FE		✓				✓
AUC	0.678	0.819	0.722	0.744	0.749	0.821

Notes: This table presents estimates of Equation (2). Driscoll and Kraay (1998) standard errors in parentheses with a bandwidth of three years to allow for residual correlation within and across banks in proximate years. *,**, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table A.3: *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	0.11*	0.11*	0.05	-0.00	-0.01	0.02
	(0.06)	(0.06)	(0.07)	(0.06)	(0.06)	(0.06)
Noncore funding	0.38	0.51	-0.14	-0.16	-0.18	0.24
	(0.67)	(0.63)	(0.76)	(0.76)	(0.76)	(0.66)
Surplus/Equity × Noncore funding	0.68	0.08	0.69	1.19	1.05	0.55
	(1.48)	(1.43)	(1.54)	(1.53)	(1.53)	(1.53)
Liquid Assets/Assets	-0.21	0.16***	-0.23	-0.22	-0.20	0.15***
	(0.16)	(0.05)	(0.22)	(0.18)	(0.21)	(0.05)
Deposits/Assets	0.14	0.11	-0.07	0.03	0.03	0.14
	(0.12)	(0.10)	(0.13)	(0.16)	(0.13)	(0.13)
Asset Growth (3 years)	0.04	0.10**	0.08	0.05	0.07	0.09*
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Macro conditions:						
NB failure rate			0.25		-0.18	
			(1.87)		(1.77)	
NB run rate			2.78		5.72	
			(8.48)		(8.22)	
Stock market return			-0.24**			
			(0.12)			
Real GDP growth			0.36		0.26	
			(0.46)		(0.41)	
Local conditions:						
Run on other bank in same city				1.75***	1.74***	1.54***
				(0.56)	(0.56)	(0.47)
Local business failure rate				2.80**	1.47	2.14
				(1.25)	(2.46)	(2.97)
N	286382	286382	242910	239863	239863	239863
Mean dep. var	.16	.16	.17	.17	.17	.17
Year FE		✓				✓
AUC	0.577	0.810	0.670	0.679	0.713	0.817

Notes: This table presents estimates of Equation (2). Driscoll and Kraay (1998) standard errors in parentheses with a bandwidth of three years to allow for residual correlation within and across banks in proximate years. *,**, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table A.4: *Predictability of Failure with Bank Run Based on Fundamentals, Runs on Other Banks, and Macroeconomic Variables*

Dependent variable	Failure with run in $t+1$					
	(1)	(2)	(3)	(4)	(5)	(6)
Bank fundamentals:						
Surplus/Equity	-0.30***	-0.34**	-0.35**	-0.32***	-0.38**	-0.38**
	(0.11)	(0.14)	(0.15)	(0.12)	(0.16)	(0.16)
Noncore funding	8.28***	8.29***	7.82***	7.93***	7.74***	8.25***
	(2.50)	(2.42)	(2.53)	(2.69)	(2.54)	(2.67)
Surplus/Equity × Noncore funding	-8.00***	-9.48***	-8.55***	-7.64***	-8.14***	-9.05***
	(1.79)	(2.04)	(2.05)	(1.98)	(2.01)	(2.22)
Liquid Assets/Assets	-0.27***	-0.27	-0.36**	-0.32**	-0.35**	-0.30
	(0.10)	(0.17)	(0.15)	(0.13)	(0.16)	(0.18)
Deposits/Assets	0.49*	0.30**	0.26	0.43	0.34	0.26*
	(0.27)	(0.12)	(0.20)	(0.28)	(0.21)	(0.14)
Asset Growth (3 years)	-0.22*	-0.13	-0.10	-0.17	-0.10	-0.14
	(0.12)	(0.09)	(0.10)	(0.11)	(0.10)	(0.11)
Macro conditions:						
NB failure rate			-1.34		-1.91	
			(2.91)		(2.93)	
NB run rate			-1.22		3.60	
			(9.46)		(9.82)	
Stock market return			-0.36**			
			(0.17)			
Real GDP growth			-0.27		-0.39	
			(0.35)		(0.35)	
Local conditions:						
Run on other bank in same city				0.91**	0.90***	0.79**
				(0.34)	(0.33)	(0.31)
Local business failure rate				6.34***	0.07	-0.79
				(2.23)	(2.93)	(3.13)
N	286382	286382	242910	239863	239863	239863
Mean dep. var	.15	.15	.16	.16	.16	.16
Year FE		✓				✓
AUC	0.814	0.871	0.850	0.864	0.868	0.888

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	Failure in $t+1$					
	(1)	(2)	(3)	(4)	(5)	(6)
Bank fundamentals:						
Surplus/Equity	-1.75***	-2.00***	-2.05***	-1.82***	-2.12***	-2.14***
	(0.53)	(0.61)	(0.68)	(0.56)	(0.74)	(0.70)
Noncore funding	70.87***	67.66***	70.89***	71.95***	70.65***	71.32***
	(18.24)	(16.71)	(18.26)	(19.66)	(18.61)	(18.37)
Surplus/Equity × Noncore funding	-96.06***	-102.43***	-106.55***	-101.59***	-105.23***	-106.96***
	(21.51)	(23.59)	(25.01)	(24.67)	(25.24)	(26.14)
Liquid Assets/Assets	-0.48	-2.05***	-1.59**	-1.08**	-1.63**	-2.14***
	(0.48)	(0.70)	(0.65)	(0.53)	(0.67)	(0.74)
Deposits/Assets	2.94**	1.17*	1.36*	2.46**	1.59*	1.20*
	(1.19)	(0.59)	(0.79)	(1.20)	(0.80)	(0.68)
Asset Growth (3 years)	-2.13***	-1.42***	-1.30**	-1.79**	-1.27**	-1.55**
	(0.79)	(0.53)	(0.59)	(0.75)	(0.61)	(0.61)
Macro conditions:						
NB failure rate			9.29		6.17	
			(12.25)		(14.19)	
NB run rate			-43.39		-15.37	
			(31.90)		(37.87)	
Stock market return			-1.93***			
			(0.60)			
Real GDP growth			-4.26*		-4.81*	
			(2.24)		(2.45)	
Local conditions:						
Run on other bank in same city				2.73***	2.66***	2.43***
				(0.77)	(0.70)	(0.65)
Local business failure rate				46.19***	8.67	1.71
				(6.73)	(15.35)	(15.43)
N	286382	286382	242910	239863	239863	239863
Mean dep. var	.81	.81	.91	.92	.92	.92
Year FE		✓				✓
AUC	0.868	0.896	0.892	0.891	0.897	0.907

Notes: This table presents estimates of Equation (2).Driscoll and Kraay (1998) standard errors in parentheses with a bandwidth of three years to allow for residual correlation within and across banks in proximate years. *,**, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table A.6: ***Bank Runs, Failures, and Fundamentals: Detailed Specifications***

Dependent variable	Failure in t							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Run	0.37***	0.56***	0.28***	0.22***	0.38***	0.28***	0.42***	0.43***
	(0.056)	(0.080)	(0.044)	(0.030)	(0.098)	(0.050)	(0.081)	(0.080)
Surplus/Equity		-0.024***				-0.0085***	-0.025***	-0.032***
		(0.0084)				(0.0019)	(0.0091)	(0.012)
Surplus/Equity × Run		-0.56***				-0.40***	-0.51***	-0.51***
		(0.11)				(0.089)	(0.082)	(0.081)
Noncore funding			0.37***			0.14***	0.37***	0.31***
			(0.11)			(0.039)	(0.11)	(0.082)
Noncore funding× Run			1.86***			1.97**	1.70***	1.68***
			(0.36)			(0.82)	(0.37)	(0.37)
OREO/Loans				0.100***		0.075***		
				(0.030)		(0.019)		
OREO/Loans× Run				2.13***		1.34*		
				(0.68)		(0.68)		
Liquid/Assets					-0.00059	0.0020	0.012	-0.022***
					(0.0063)	(0.0017)	(0.0076)	(0.0074)
Liquid/Assets × Run					-0.056	0.21*	0.12	0.089
					(0.18)	(0.11)	(0.12)	(0.11)
Observations	268483	268483	268483	86279	268483	86278	268483	268483
R^2	0.055	0.063	0.092	0.094	0.055	0.12	0.098	0.12
State FE						✓		✓
Year FE						✓		✓
Sample	1865-1934	1865-1934	1865-1934	1865-1904	1865-1934	1865-1904	1865-1934	1865-1934

Notes: This table presents estimates of Equation (3). Driscoll and Kraay (1998) standard errors in parentheses with a bandwidth of three years to allow for residual correlation within and across banks in proximate years. *,**, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table A.7: ***Bank Runs, Failures, and Fundamentals: Different Time Periods***

Dependent variable	Failure in t					
	(1)	(2)	(3)	(4)	(5)	(6)
Run	0.43***	0.35***	0.83***	0.85***	0.42***	0.52*
	(0.080)	(0.075)	(0.16)	(0.038)	(0.080)	(0.24)
Surplus/Equity	-0.032***	-0.0072***	-0.024***	-0.14***	-0.017***	-0.084*
	(0.012)	(0.0016)	(0.0070)	(0.023)	(0.0051)	(0.036)
Surplus/Equity × Run	-0.51***	-0.48***	-0.83***	-0.43***	-0.59***	-0.32*
	(0.081)	(0.11)	(0.20)	(0.067)	(0.095)	(0.16)
Noncore funding	0.31***	0.12***	0.24***	0.70**	0.23***	0.87***
	(0.082)	(0.036)	(0.059)	(0.16)	(0.051)	(0.11)
Noncore funding× Run	1.68***	2.13***	0.72	0.42	1.74***	1.06
	(0.37)	(0.71)	(0.50)	(0.36)	(0.57)	(0.69)
Liquid/Assets	-0.022***	-0.0012	-0.014***	-0.054**	0.0024	0.047**
	(0.0074)	(0.0017)	(0.0035)	(0.014)	(0.0027)	(0.017)
Liquid/Assets × Run	0.089	0.11	-0.56	-0.65***	0.14	-0.16
	(0.11)	(0.15)	(0.32)	(0.084)	(0.11)	(0.31)
Observations	268483	133290	109603	25590	234978	33505
R^2	0.12	0.11	0.091	0.15	0.099	0.12
State FE	✓	✓	✓	✓		
Year FE	✓	✓	✓	✓		
Sample	1865-1934	1865-1913	1914-1928	1929-1934	No Crisis	Banking Crises

Notes: This table presents estimates of Equation (3). Driscoll and Kraay (1998) standard errors in parentheses with a bandwidth of three years to allow for residual correlation within and across banks in proximate years. *,**, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table A.8: ***Role of Clearinghouses in the Pass-Through of Runs to Failure***

Dependent variable	Failure in t+1			
	(1)	(2)	(3)	(4)
Run	0.39***	0.29***	0.37***	0.44***
	(0.050)	(0.036)	(0.043)	(0.067)
Clearinghouse City	-0.0024**	0.00050	-0.0020*	-0.0075*
	(0.0010)	(0.00040)	(0.0011)	(0.0035)
Clearinghouse City × Run	-0.086**	-0.079**	-0.14**	-0.016
	(0.042)	(0.035)	(0.052)	(0.031)
Observations	278032	133290	239711	38321
R^2	0.056	0.077	0.065	0.048
Mean dep. var.	0.0083	0.0030	0.0049	0.029
Sample		<1914	No Crisis	Banking Crisis

Notes: This table presents estimates of Equation (3). Driscoll and Kraay (1998) standard errors in parentheses with a bandwidth of three years to allow for residual correlation within and across banks in proximate years. *,**, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

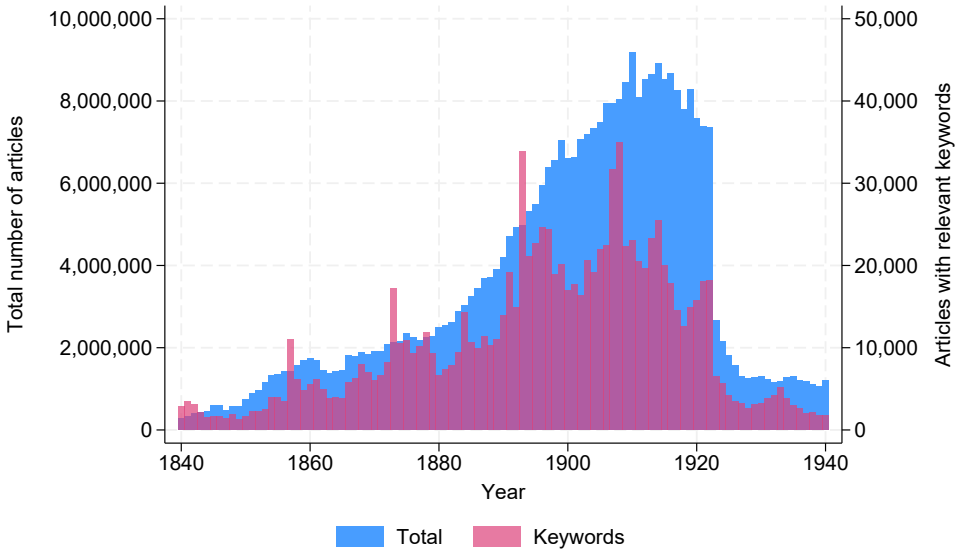
B Constructing the Bank Distress Episodes Dataset

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”

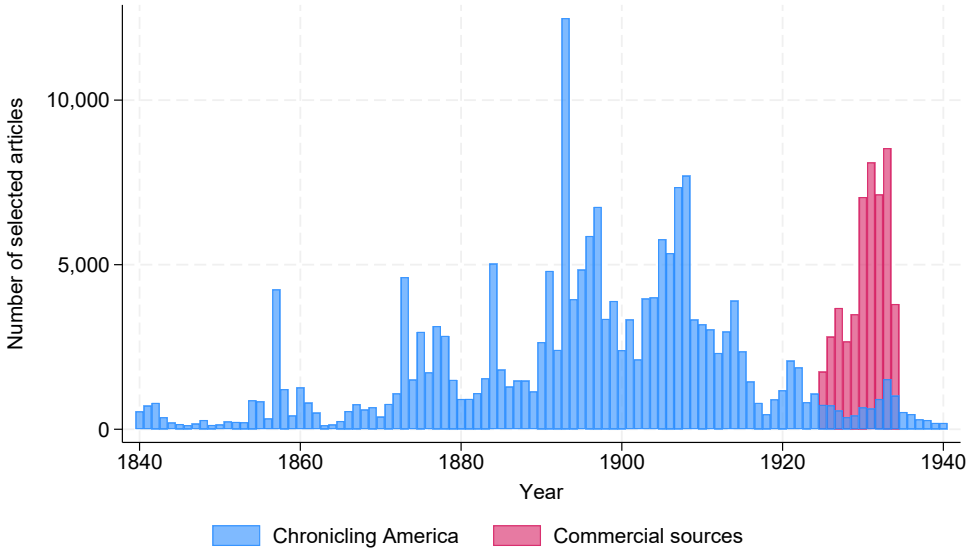
Notes: Matching is case-insensitive. To avoid false positives, unrelated words are first removed from the text before searching. These include geographical features (e.g., “river bank”, “snow bank”), proper names (e.g., “Albert Banks”), and common but unrelated financial terms (e.g., “bank loans,” “banknote”).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



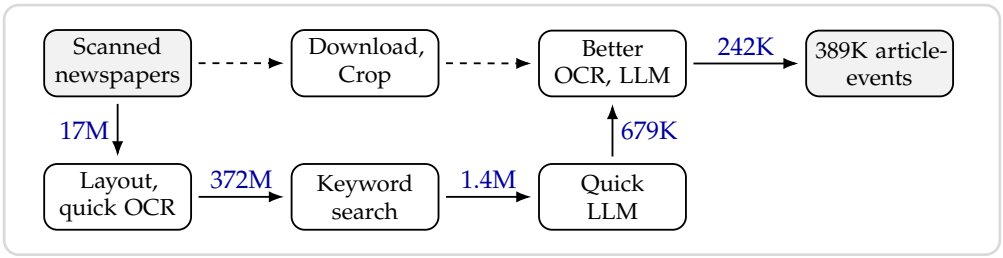
Notes: The left axis depicts total articles available per year in "Chronicling America", while the right axis shows the number of articles with keywords related to bank distress events (see Appendix Table B.1). The scale of the left axis is 200 times larger than that of the right axis. On average across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

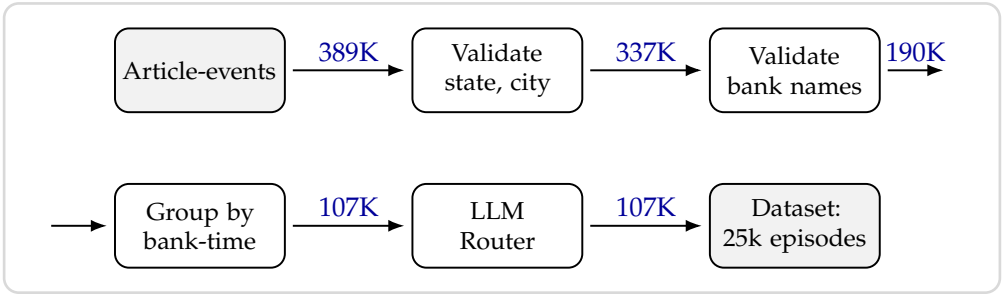


Notes: This figure shows the number of newspaper articles per year included in our final sample of newspaper articles. The two requirements for inclusion are i) having at least one keyword related to bank distress events (see Table B.1) and ii) being flagged by an LLM as related to a bank distress event (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[1]. Here we face three problems: first, the U.S. has way more cities and towns than states. Second, towns frequently changed names over time. Third, towns close to large cities could merge into the cities to become suburbs.

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

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

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

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

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

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

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

[1]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, Luck and Verner, 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.

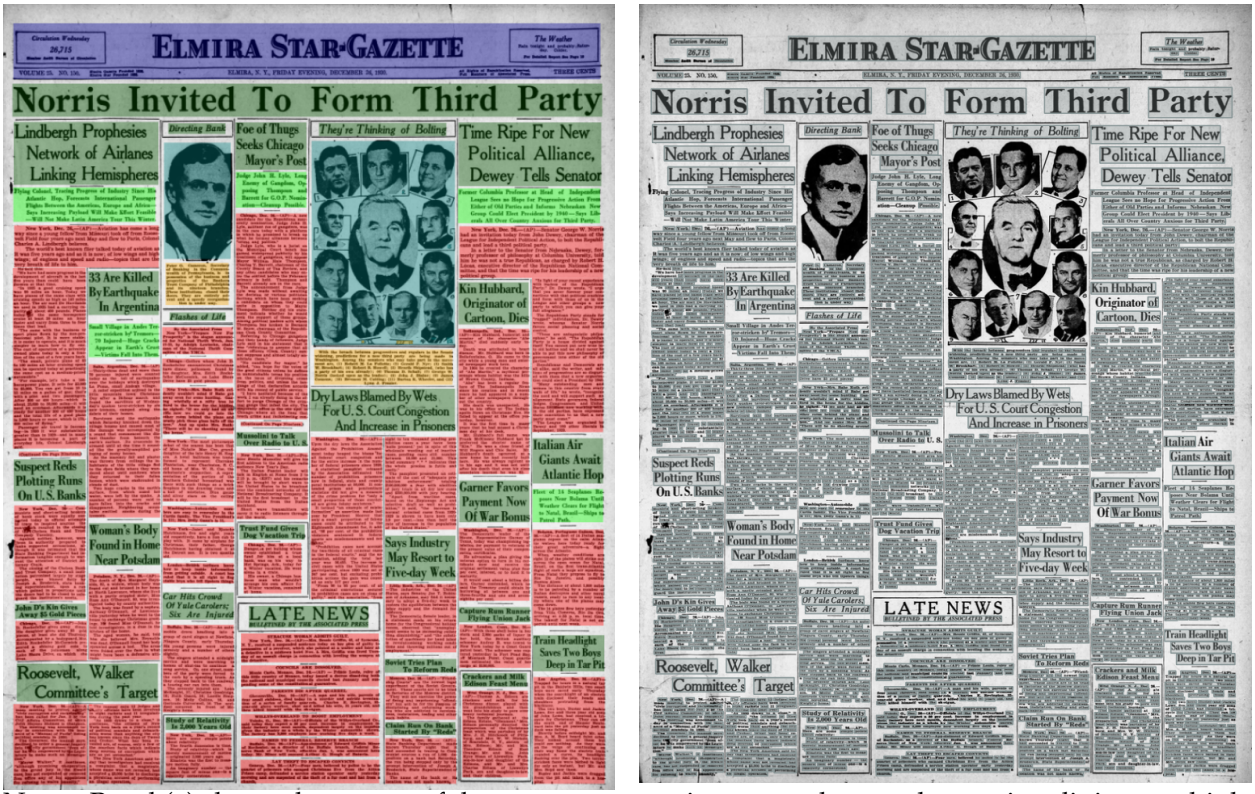
We use these datasets to create a validated list of U.S. banks, which are the main input to our `bank-census` Python package.

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*

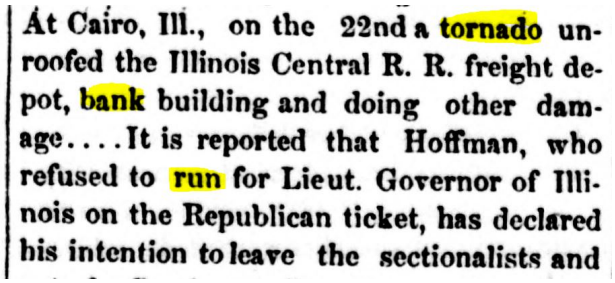
(a) ***Layout:*** *Page segmentation* **(b)** ***OCR:*** *Text extraction*



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).

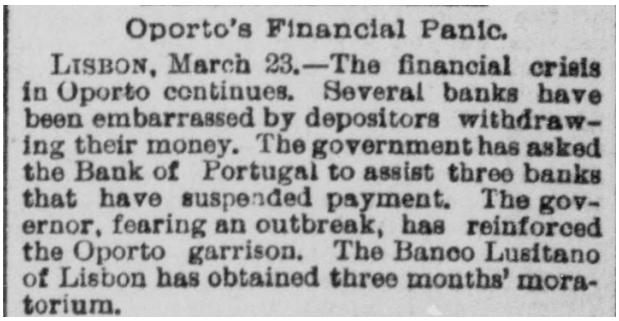
Figure B.5: *Examples of False Positives Flagged by Keywords and Excluded by LLMs*

(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

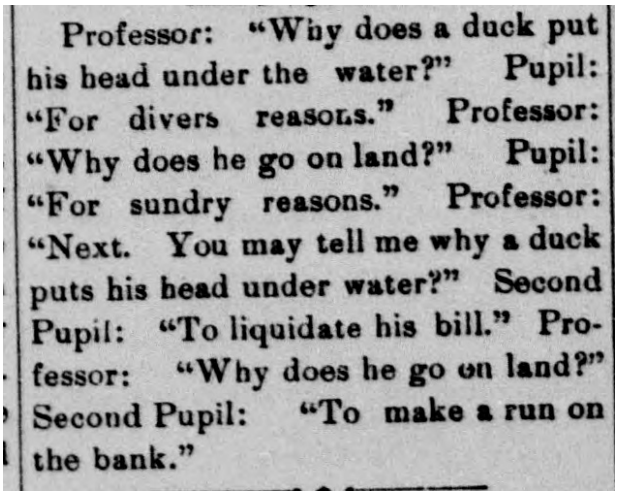
(b) *Foreign bank run*



Oporto's Financial Panic.

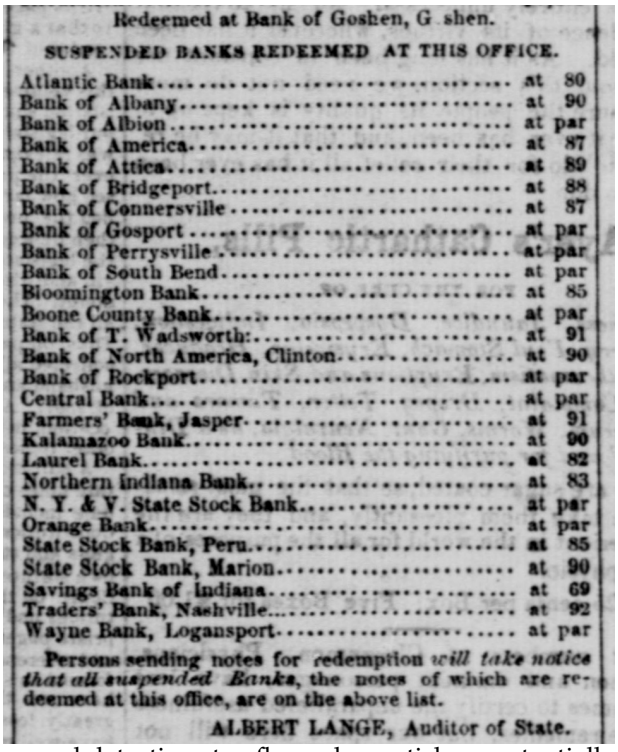
LISBON, March 23.—The financial crisis in Oporto continues. Several banks have been embarrassed by depositors withdrawing their money. The government has asked the Bank of Portugal to assist three banks that have suspended payment. The governor, fearing an outbreak, has reinforced the Oporto garrison.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

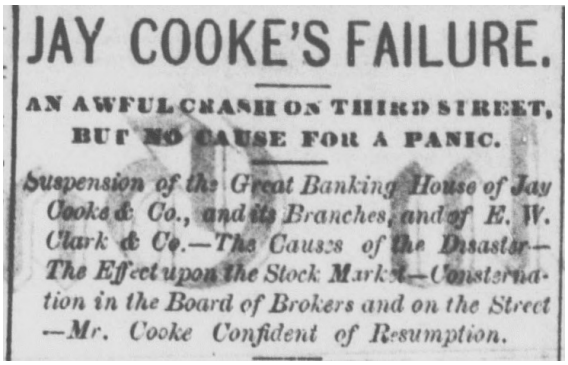
Persons sending notes for redemption *will take notice that all suspended Banks*, the notes of which are redeemed at this office, are on the above list.

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)*

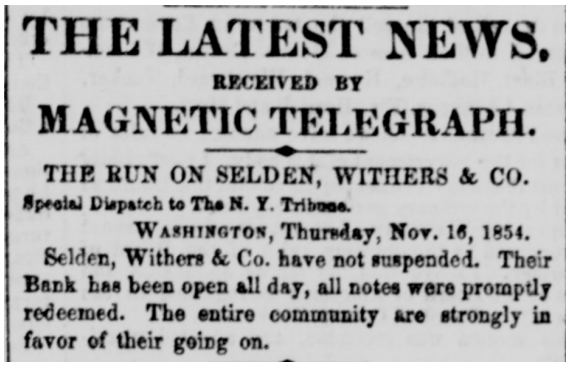


JAY COOKE'S FAILURE.

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.

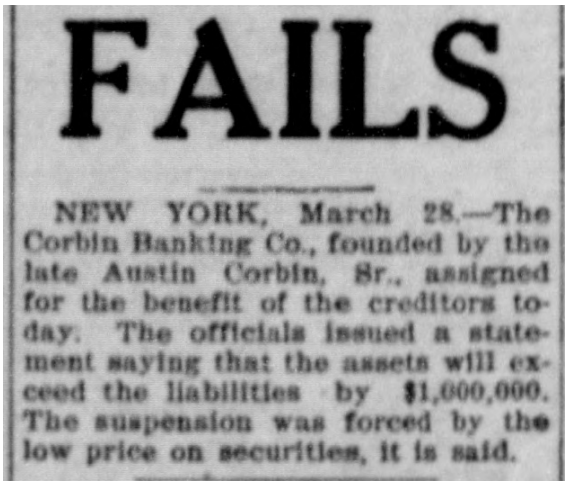
THE RUN ON SELDEN, WITHERS & CO.

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.

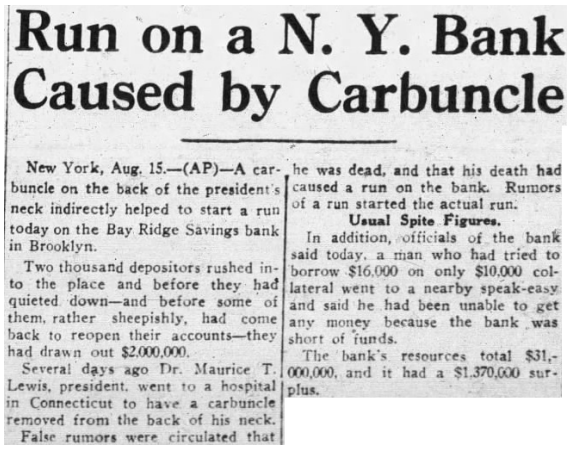
(c) *Bank failure (1907)*



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.

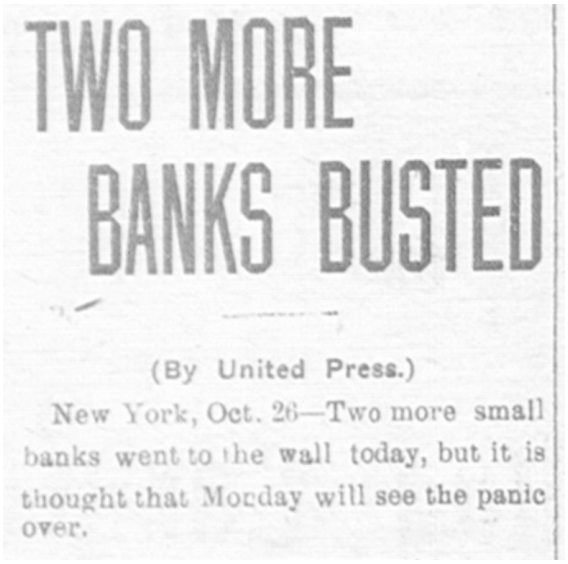
Several days ago Dr. Maurice T. Lewis, president, went to a hospital in Connecticut to have a carbuncle removed from the back of his neck. False rumors were circulated that he was dead, and that his death had caused a run on the bank. Rumors of a run started the actual run.

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: *Examples from 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.

C Details on Other Data

C.1 Bradstreet's Trade at a Glance

Source. The weekly business and financial journal *Bradstreet's* published a summary of economic conditions at the city level for major North American cities called Trade at a Glance (TAAG). Figure C.1 provides an example of the raw data. Building on Correia, Luck and Verner (2022), we digitize these tables for all years they are available, from 1917 to March 1933. From March 1933 through 1935, *Bradstreet's* provides short (one or two-paragraph) descriptions of business conditions, from which we extract key phrases. Data from March 1933 onward is available at a monthyl frequency. Given the sample break, we verify that results are robust to excluding the data after March 1933.

Conversion to numeral score for TAAG tables. For 1917-1933, the TAAG tables provide a short description of conditions in various sectors in the city. We convert the text into an integer value from 1 (bad conditions), 2 (fair conditions), and 3 (good conditions). The exact classification is given in Table C.1.

Conversion to numeral score for TAAG paragraphs. For 1933-1935, we search the text for whether a sector is described with any of the keywords given in Table C.1. We then apply the same classification.

Sample. Throughout the 1917 to 1935 period, Bradstreet's covers 119 distinct cities. However, some cities only enter the sample occasionally. We therefore focus on a sample of 30 cities with consistent coverage throughout the sample. Because even these cities can occasionally enter and exit the sample we fill missing values forward. For our analysis at the city level, we also take a seven-week moving average to smooth out the discrete changes in the index. We verify that the main results are not sensitive to forward-filling and smoothing.

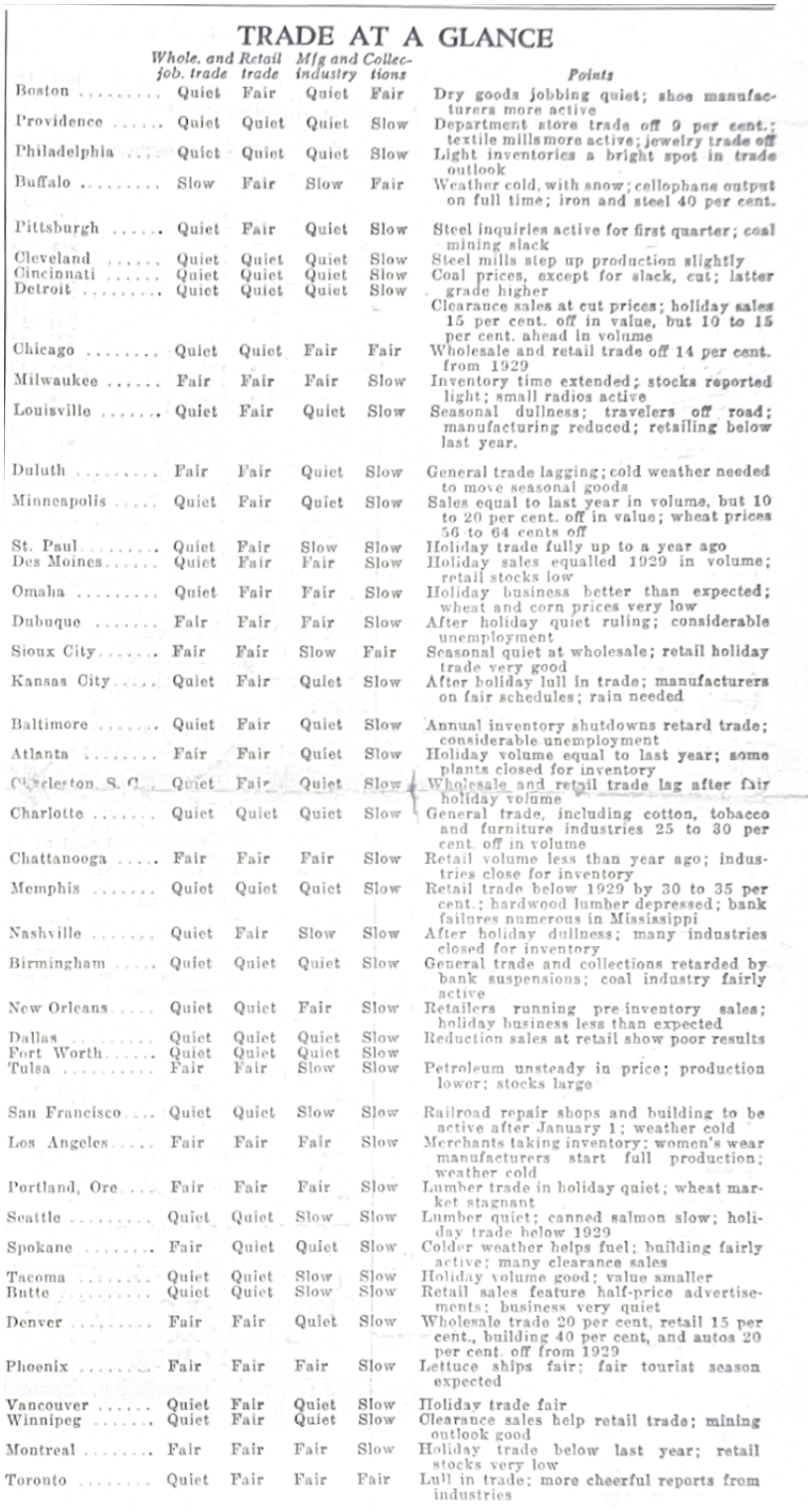
Comparison with industrial production. To validate the usefulness of our local economic activity index based on *Bradstreet's* TAAG, we compare the manufacturing index to industrial production (IP) estimates from Miron and Romer (1990). Since IP is monthly at the national level, we take a cross-city average of the TAAG manufacturing index in each month. Moreover, since IP contains a trend, while TAAG refers to cyclical conditions, we consider the year-on-year change in log industrial production and the deviation of log industrial production from the one-sided three-year moving average.

Figure C.2 reports the comparison. The correlation is quite high. For example, the R^2 between the TAAG manufacturing index and IP's deviation from its three-year moving average is 0.59. Moreover, the TAAG manufacturing index clearly captures the 1920-21 recession and the downturn and recovery in the Great Depression.

Table C.1: *Bradstreet's TAAG Classification*

Bad (cat=1)	Fair (cat=2)	Good (cat=3)
75 percent	better	active
backward	better outlook	brisk
blackening	cautions	enlarging
contracted	fair	fairly active
curtailed	fair activity	gaining
curtailing	improved	good
disturbed	improving	improvement
dull	irregular	increased
hampered	normal	increasing
hesitating	readjusting	more active
inactive	shifting	picking up
interrupted	spotty	very active
lagging	steady	
less active	unsettled	
paralyzed	varying	
poor		
quiet		
quieter		
reduced		
restricted		
retarded		
slackened		
slow		
slower		
slowing up		
strikes hurtful		
suspended		
very dull		
very quiet		
waiting		

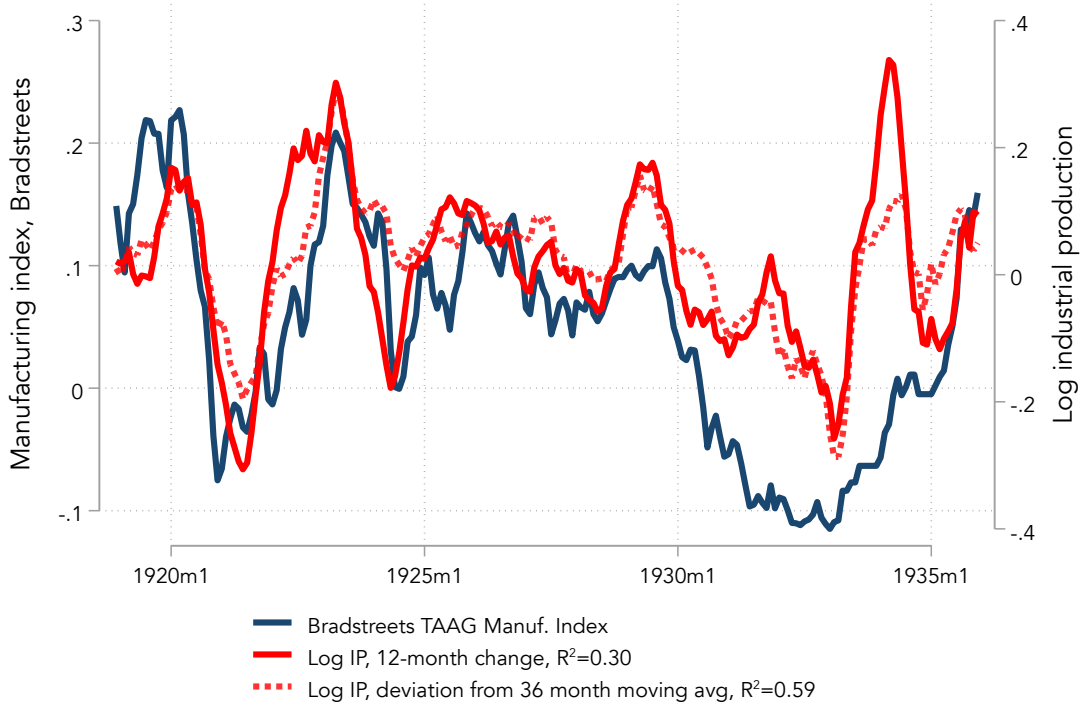
Figure C.1: *Bradstreet's Trade at a Glance: Example from January 3, 1931*



TRADE AT A GLANCE

	Whole. and job. trade	Retail trade	Mfg and industry	Collections	Points
Boston	Quiet	Fair	Quiet	Fair	Dry goods jobbing quiet; shoe manufacturers more active
Providence	Quiet	Quiet	Quiet	Slow	Department store trade off 9 per cent.; textile mills more active; jewelry trade off
Philadelphia	Quiet	Quiet	Quiet	Slow	Light inventories a bright spot in trade outlook
Buffalo	Slow	Fair	Slow	Fair	Weather cold, with snow; cellophane output on full time; iron and steel 40 per cent.
Pittsburgh	Quiet	Fair	Quiet	Slow	Steel inquiries active for first quarter; coal mining slack
Cleveland	Quiet	Quiet	Quiet	Slow	Steel mills step up production slightly
Cincinnati	Quiet	Quiet	Quiet	Slow	Coal prices, except for slack, cut; latter grade higher
Detroit	Quiet	Quiet	Quiet	Slow	Clearance sales at cut prices; holiday sales 15 per cent. off in value, but 10 to 15 per cent. ahead in volume
Chicago	Quiet	Quiet	Fair	Fair	Wholesale and retail trade off 14 per cent. from 1929
Milwaukee	Fair	Fair	Fair	Slow	Inventory time extended; stocks reported light; small radios active
Louisville	Quiet	Fair	Quiet	Slow	Seasonal dullness; travelers off road; manufacturing reduced; retailing below last year.
Duluth	Fair	Fair	Quiet	Slow	General trade lagging; cold weather needed to move seasonal goods
Minneapolis	Quiet	Fair	Quiet	Slow	Sales equal to last year in volume, but 10 to 20 per cent. off in value; wheat prices 56 to 64 cents off
St. Paul	Quiet	Fair	Slow	Slow	Holiday trade fully up to a year ago
Des Moines	Quiet	Fair	Fair	Slow	Holiday sales equalled 1929 in volume; retail stocks low
Omaha	Quiet	Fair	Fair	Slow	Holiday business better than expected; wheat and corn prices very low
Dubuque	Fair	Fair	Fair	Slow	After holiday quiet ruling; considerable unemployment
Sioux City	Fair	Fair	Slow	Fair	Seasonal quiet at wholesale; retail holiday trade very good
Kansas City	Quiet	Fair	Quiet	Slow	After holiday lull in trade; manufacturers on fair schedules; rain needed
Baltimore	Quiet	Fair	Quiet	Slow	Annual inventory shutdowns retard trade; considerable unemployment
Atlanta	Fair	Fair	Quiet	Slow	Holiday volume equal to last year; some plants closed for inventory
Charleston, S. C.	Quiet	Fair	Quiet	Slow	Wholesale and retail trade lag after fair holiday volume
Charlotte	Quiet	Quiet	Quiet	Slow	General trade, including cotton, tobacco and furniture industries 25 to 30 per cent. off in volume
Chattanooga	Fair	Fair	Fair	Slow	Retail volume less than year ago; industries close for inventory
Memphis	Quiet	Quiet	Quiet	Slow	Retail trade below 1929 by 30 to 35 per cent.; hardwood lumber depressed; bank failures numerous in Mississippi
Nashville	Quiet	Fair	Slow	Slow	After holiday dullness; many industries closed for inventory
Birmingham	Quiet	Quiet	Quiet	Slow	General trade and collections retarded by bank suspensions; coal industry fairly active
New Orleans	Quiet	Quiet	Fair	Slow	Retailers running pre-inventory sales; holiday business less than expected
Dallas	Quiet	Quiet	Quiet	Slow	Reduction sales at retail show poor results
Fort Worth	Quiet	Quiet	Quiet	Slow	
Tulsa	Fair	Fair	Slow	Slow	Petroleum unsteady in price; production lower; stocks large
San Francisco	Quiet	Quiet	Slow	Slow	Railroad repair shops and building to be active after January 1; weather cold
Los Angeles	Fair	Fair	Fair	Slow	Merchants taking inventory; women's wear manufacturers start full production; weather cold
Portland, Ore.	Fair	Fair	Fair	Slow	Lumber trade in holiday quiet; wheat market stagnant
Seattle	Quiet	Quiet	Slow	Slow	Lumber quiet; canned salmon slow; holiday trade below 1929
Spokane	Fair	Quiet	Quiet	Slow	Colder weather helps fuel; building fairly active; many clearance sales
Tacoma	Quiet	Quiet	Slow	Slow	Holiday volume good; value smaller
Butte	Quiet	Quiet	Slow	Slow	Retail sales feature half-price advertisements; business very quiet
Denver	Fair	Fair	Quiet	Slow	Wholesale trade 20 per cent, retail 15 per cent., building 40 per cent, and autos 20 per cent. off from 1929
Phoenix	Fair	Fair	Fair	Slow	Lettuce ships fair; fair tourist season expected
Vancouver	Quiet	Fair	Quiet	Slow	Holiday trade fair
Winnipeg	Quiet	Fair	Quiet	Slow	Clearance sales help retail trade; mining outlook good
Montreal	Fair	Fair	Fair	Slow	Holiday trade below last year; retail stocks very low
Toronto	Quiet	Fair	Fair	Fair	Lull in trade; more cheerful reports from industries

Figure C.2: *Comparing Bradstreet's Trade at a Glance Manufacturing Index and Industrial Production*



Notes: This figure compares the national monthly average of our manufacturing index constructed from digitized *Bradstreet's* Trade at a Glance tables with industrial production. Industrial production is detrended using the year-on-year log change or the deviation from a three-year moving average.